Behavioural robustness and the distributed mechanisms hypothesis

Jose A. Fernandez-Leon

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Declaration

I hereby declare that this thesis has not been submitted, either in the same or different form, to this or any other university for a degree.

Signature:

Preface

The work reported in this thesis is my own work. Some of the material in this work has been published before the submission of the thesis in international journals and peer-reviewed conference proceedings. The work developed in [Fernandez-Leon & Di Paolo, 2007] and continued in [Fernandez-Leon & Di Paolo, 2008] encompasses analyses and discussions given in Chapter 5. The work in [Fernandez-Leon & Froese, 2010] and [Fernandez-Leon, sub. 2010c] is extended in Chapter 8. Discussions and experiments described in Chapter 7 have been published in a peer reviewed Journal (see [Fernandez-Leon, 2011]). Work in Chapter 6 is awaiting evaluation in another peer reviewed Journal (see [Fernandez-Leon, sub. 2010a]). Finally, discussions in [Fernandez-Leon, sub. 2010b] are intended for furthering the overall understanding of various bio-inspired-phenomena reported here. All seven articles, experiments, analyses and work not already published but reported for this thesis have been carried out during my doctoral studies.

The 'Dynamica' software package developed by Randall Beer was used for part of the dynamical analyses. This package is available on-line from Beer's website.

Acknowledgements

Like many human activities that seek to explore, intrigue, and inform, the whole task of a scientific work like this thesis is to create a 'good, clear, coherent, and easy to read story.' Thanks to Dr. Ezequiel Di Paolo for his explanations on how to create a research story. To Dr. Inman Harvey for the 'little Inman on my shoulders' that demanded simple and highly critical thought of every single concept and explanation in this thesis. To Dr. Phil Husbands for his focused and precise comments during my annual meeting reviews that guided some of my thought during my research. Thanks to him also for supporting my requests with very helpful bursaries when things were tight, and for facilitating some of my valuable conference excursions.

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I must also acknowledge the contribution of members of the Centre for Computational Neuroscience and Robotics (CCNR) for first-class discussions, and for good moments far from research. The contents of this thesis have also benefited from fruitful discussions with Tom Froese, Lucas Wilkins, Bruno Santos, Renan Moioli, Allister Furey, Edgar Bermudez Contreras, Xabier Barandiaran, and Nicholas Tomko. A special mention should also be made of Greg Studer for our discussions in how to clarify the ideas within. Thanks also to Dr. Paul Graham for statistical support. To anonymous reviewers and other members of CCNR, including former ones, for good chats and friendly atmosphere. Again, my thanks to all of them.

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Outstanding thanks to Andrea for supporting and motivating me to reach my goals. Many thanks to Andrea for her solid determination over our 'Brightonian stage'. Finally, but not the last, many thanks to my mother Anna and my brother Daniel (Dany) who, together with my great grandparents Nicolás and Paula, deserve, as always, my deepest gratitude.

Thanks to all of them for sustaining, financing and otherwise, my 'UK PhD journey.'

Dedicated to Andrea, Anna, Dany, Nicolás and Paula.

Dedicated to blue-sky scientists who aim
to discover how the world works.

Behavioural robustness and the distributed mechanisms hypothesis

Jose A. Fernandez-Leon

Summary

A current challenge in neuroscience and systems biology is to better understand properties that allow organisms to exhibit and sustain appropriate behaviours despite the effects of perturbations (behavioural robustness). There are still significant theoretical difficulties in this endeavour, mainly due to the context-dependent nature of the problem. Biological robustness, in general, is considered in the literature as a property that emerges from the internal structure of organisms, rather than being a dynamical phenomenon involving agent-internal controls, the organism body, and the environment. Our hypothesis is that the capacity for behavioural robustness is rooted in dynamical processes that are distributed between agent 'brain', body, and environment, rather than warranted exclusively by organisms' internal mechanisms. Distribution is operationally defined here based on perturbation analyses.

Evolutionary Robotics (ER) techniques are used here to construct four computational models to study behavioural robustness from a systemic perspective. Dynamical systems theory provides the conceptual framework for these investigations. The *first model* evolves situated agents in a goal-seeking scenario in the presence of neural noise perturbations. Results suggest that evolution implicitly selects neural systems that are noise-resistant during coupling behaviour by concentrating search in regions of the fitness landscape that retain functionality for goal approaching. The *second model* evolves situated, dynamically limited agents exhibiting minimal-cognitive behaviour (categorization task). Results indicate a small but significant tendency toward better performance under most types of perturbations by agents showing further cognitive-behavioural dependency on their environments. The *third model* evolves experience-dependent robust behaviour in embodied, one-legged walking agents. Evidence suggests that robustness is rooted in both internal and external dynamics, but robust motion emerges always from the system-in-coupling. The *fourth model* implements a historically dependent, mobile-object tracking task under sensorimotor perturbations. Results indicate two different modes of distribution, one in which inner controls necessarily depend on a set of specific environmental factors to exhibit behaviour, then these controls will be more vulnerable to perturbations on that set, and another for which these factors are equally sufficient for behaviours. Vulnerability to perturbations depends on the particular distribution.

In contrast to most existing approaches to the study of robustness, this thesis argues that behavioural robustness is better understood in the context of agent-environment dynamical couplings, not in terms of internal mechanisms. Such couplings, however, are not always the full determinants of robustness. Challenges and limitations of our approach are also identified for future studies.

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Contents

"(...) as soon as I had finished the entire course of study, at the close of which it is customary to be admitted into the Doctor degree, I completely changed my opinion. For I found myself involved in so many doubts and errors that I was convinced I had advanced no further in all my attempts at learning, than the discovery at every turn of my own ignorance."

René Descartes, Discourse on Method, 1637

Chapter 1

Introduction

"... lo voy a pre-estudiar."

Nicolás Fellenz

"In an open system, such as our bodies represent, compounded of unstable material and subjected continuously to disturbing conditions, constancy is itself evidence that agencies are acting or ready to act, to maintain this constancy."

Walter B. Cannon, 1939 (from Ashby, 1960, p. 64).

1.1 Overview of this thesis

Organisms' surroundings certainly play an important role in shaping actions, while behaviour is by no means solely defined internally. The responses to particular situations in the environment (e.g. the presence of poisoned food where the organism cannot sense the involved risk of eating it), for instance, *cannot* be explained only in terms of stimuli involved or internal structure on dynamics. The very same living being may behave in completely different ways when presented with seemingly identical stimuli at two different moments or places [Beer, 2004a]. In one case, the food may be hungrily consumed, while in a different moment the organism may avoid the food because it has learnt the risk involved [Beer & Chiel, 1990]. As Beer and Chiel (1990) indicate, to account for these differences behavioural scientists hypothesize internal states or drive which changes an organism's response to its environment. Maturana and Varela (1987) also point out that the ability of an organism to draw distinctions through its selective response to perturbations is a hallmark of *cognitive behaviour*.

The aim of this thesis is to understand behaviours that greatly outlast any initiating stimulus as processes that arise from agent-environment dynamics. The purpose of this understanding is to examine how behavioural patterns emerge and how we can control them. More specifically, this work analyses the dynamical coupling between modelled control systems (brain), bodies, and environments under the influence of internal and external factors (perturbations) disturbing the exhibition of behaviours, i.e. actions of an agent in the environment.

Because an agent is not just an assembly of components defining a static structure, the study of properties of the coupled agent-environment system may have an impact on future theories on how biological organisms reach robustness [Kitano, 2004a, 2006, 2007]. This thesis is different from other works in theoretical neuroscience and systems biology in that it promotes a change of perspective on robustness from being solely internally generated (i.e. a property of the internal structure of organisms) towards a dynamical phenomenon involving agent-internal control (or inner control), the agent body and the environment. The following section gives a brief description of the context of this thesis.

1.1.1 A holistic understanding of robustness

Despite the lack of a formal definition, robustness usually refers to the continuation of function in the presence of perturbations [Kitano, 2004a, 2007]. Robustness is a *systemic* property commonly attributed to living organisms [Stelling *et al.*, 2004]. When an organism performs a task, components or mechanisms in the organism cooperate to exhibit the appropriate actions. If internal and external factors negatively affect these mechanisms, then malfunctions in organism actions and tasks occur. A main goal of systems biology [Alon, 2006] and neuroscience is to elucidate principles that explain how living systems remain mostly functional despite perturbations. By *functional*, we mean in this thesis organisms or agents that are capable of fulfilling a purpose (e.g. a task), where the counterpart is non-functionality.

Systemic robustness usually is contextualized based on *mechanisms* promoting resistance to certain factors (or perturbations) that do not spread throughout agent-environment (including body) as a whole as we previously indicated. There are many definitions of mechanisms in the philosophy of science and biology. One influential characterization of neuro-biological mechanisms is: “mechanisms are entities and activities organized such that they are productive of regular changes from start to termination conditions” [Machamer *et al.*, 2000]. From an epistemic perspective, this definition implies that mechanisms are dynamic producers of phenomena. The conception of mechanisms that we want to highlight in this thesis is at a *dynamical* level, which ideally can be quantitatively related to behavioural robustness. These dynamical mechanisms can easily be framed using dynamical systems theory in neural-based systems controlling an agent’s body in the environment through the evolution of robust and adaptive behaviour. In fact, Kitano (2004a) indicates: “[biological robustness] is considered to be a fundamental feature of complex evolvable systems.”

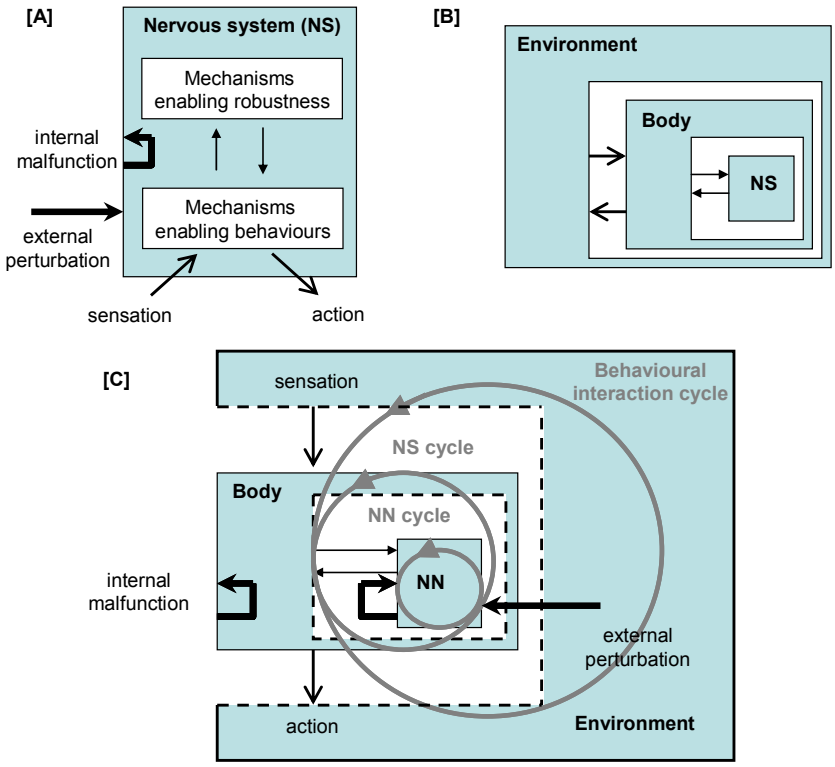

Figure 1.1 – Approaches to explaining robust and adaptive behaviour of the nervous system-body-environment system. Different dynamical loops (grey circles) contribute to behavioural robustness despite internal malfunctions and external perturbations (black thick arrows). [A] The usual understanding of behavioural robustness in neural systems, defined as the inner-based mechanistic approach. [B] The adaptive behaviour approach proposes that the nervous system (NS) is embedded within a body, which in turn is embedded within the environment. NN represents a neural network. [C] A systemic view of behavioural robustness in which the internal activity of an agent is dependent on and continuously perturbed by dynamical cycles between internal-control, body, and environment, with no necessarily separable inner mechanisms producing robustness (see [von Bertalanffy, 1968, p. 106]). Behavioural robustness as well as adaptive behaviour emerges from the interactions of all three sub-parts (nervous system, body, and environment), where the highly recursive and integrated activities of these parts are in constant flux and open to body and environment dynamics (dashed lines in [C]). Figures adapted and extended from [Chiel & Beer, 1997] and [Barandiaran, 2004].

Some structural and organizational properties of the nervous system like *modularity* and *redundancy* are thought to ensure robust performance (see [Kitano, 2004a, 2007][Krakauer, 2005][Lesne, 2008] for descriptions of these mechanisms; also see [Csete & Doyle, 2002, 2004] and [Godzik *et al.*, 2004] for descriptions of more complex mechanisms). Following definitions in [Maturana & Varela, 1987], by organization we consider "those relations that must exist among the components of a system for it to be member of a specific class"; while by structure, we refer to "the components and relations that actively constitutes a particular unity, and makes its organization real". In particular, neuroscience and cognitive science focus on the role of the nervous system in robust and adaptive behaviour, where by 'adaptive behaviour' we mean the actions in the environment of an organism that enhances its survival opportunities [Chiel & Beer,

1997]. It is also well known in neuroscience that most behaviours are *modulated by external factors* and *previous experience* of interacting with the environment. Therefore, it seems inappropriate to formulate behavioural robustness rooted only to the inner structure of organisms (see Figure 1.1-C for a graphical representation of this point).

A completely internal-mechanism-based explanation of robustness (Figure 1.1-A) creates the illusion of division between robustness mechanisms and other behavioural mechanisms, and separates the properties at coupled system level. From a theoretical viewpoint, Kitano (2002) suggests that this traditional perspective hinders understanding of the mechanistic, system-wide, basis of robustness. He argues that it is crucial to examine the structure and dynamics of living systems in a holistic way (rather than the characteristics of isolated parts of organisms) in order to have a clearer understanding of robust traits.

Similarly, recent works in theoretical and experimental neuroscience suggest that the division between behavioural mechanisms and mechanisms generating robust traits is not straightforward. For instance, robustness in a neural context is largely associated with a *distributed* and *integrated* property named 'degeneracy': the ability of elements that are structurally different to perform the same function or yield the same output [Tononi *et al.* 1999][Edelman & Gally, 2001][Macía & Solé, 2008][Whitacre, 2010] (section 2.3). Some studies in cognitive science have also discussed the role of brain, body, and environment in behaviour, rather than only concentrating on the nervous system as the sole 'behaviour producer' (Figure 1.1-B).

In the context of adaptive behaviour, Chiel and Beer (1997) (also [Chiel *et al.*, 2009]) discuss that the nervous system cannot process information not transduced by the body, or control movements are physically impossible for the body. The converse idea suggests that properties of the body may simplify complex neural processing and control problems by using different body dynamics and sensorimotor information (e.g. to keep our torso stable and conserve energy, we swing our arms backwards and forwards, and engaging in a swing/stance cycle of our legs while walking based on feet and equilibrium feedbacks). Going further, new evidence that 'the body shapes the way we think' [Pfeifer & Bongard, 2006], indicates that the full experience of the body-environment coupled dynamics continuously shapes cognitive and behavioural abilities as well as their respective mechanisms (Figure 1.1-C). Despite this broad hypothesis, we have very little idea about how internal controls in artificial and biological organisms managing the effects of perturbations are (or can be) realized at a dynamical level. Studying these mechanisms in Evolutionary Robotics (ER) [Nolfi & Floreano, 2000] can inform our understanding of what to look for in natural systems and how to build better artificial examples (see also [Floreano & Mondada, 1998]).

1.1.2 A distributed view of robustness

The accepted understanding of behavioural robustness (i.e. ability to generate a core behaviour despite perturbations) and adaptive behaviour is gradually changing from being generated by

isolated control mechanisms within organisms towards dynamical process occurring over multiple and *distributed* systemic components (see [Kitano, 2002][Calcott, 2010]). However, the word distributed in neuroscience and Artificial Intelligence (AI), for instance, still means distributed *within* the brain (i.e. like distributed parallel computation in neural networks).

A 'holistic' approach also involves behavioural and cognitive mechanisms which suggests that organisms obtain information from the coupled system dynamics in a way no dedicated, internal control system could possibly emulate [Scheier *et al.*, 1998][Pfeifer & Scheier, 2001][Pfeifer & Bongard, 2006][Espenschied *et al.*, 1996]. Combining this observation and those from section 1.1.1, however, how we can establish that distribution is not just a 'shorthand' for brain-body-environment coupling? This thesis emphasizes that distribution is a more precise context in which to discuss behavioural robustness, because we propose that if the processes that sustain behaviours are distributed (rather than centralized in the brain), a flow of information is possible between brain-body-environment processes with no two parts performing the same function.

Our hypothesis is that *the more distributed the behavioural mechanisms are between brain, body, and environment, the more chance an organism has to remain functional in the presence of perturbations affecting dynamical processes that sustain behaviours.* This hypothesis opens the question of how one measures a behavioural control system as being more distributed than another. In fact, there are different manners to account for the distribution of a control system, which depends on diverse ways in which we hypothesize that processes split between brain-body-environment. In section 2.4, we attempt ourselves to define a distribution criterion by discussing the role of functional *dependencies* between an agent's (inner) control system and (outer) environmental dynamics (including the body). These dependencies are coupled dynamics that emerge from organisms' evolution and are conceptually required for behaviour modulation (see also [Chiel & Beer, 1997]). The method developed in this thesis to address the distribution of behavioural mechanisms allows us to investigate in what specific ways the system-with-coupling can be robust. More explicitly, distribution is operationally defined in this work based on perturbation analyses as the *use* of environmental and body factors by internal (neural) control to determine agents own robust behaviour. However, further questions remain to be answered such as: does distribution always happen? If not so, when can we identify such a distribution? Finally, how to induce the distribution of behavioural mechanisms in small (artificial) systems to explore our hypothesis? In Chapter 2 we discuss possible answers from the perspective of embodied, situated, and dynamical agents (Chapter 3), looking for foundations of the distribution of mechanisms in literature.

1.1.3 Robustness and distributed behaviour in Evolutionary Robotics

One effort to understand how the distribution of behavioural mechanisms works comes from ER — a research methodology introduced by Husbands and Harvey (1992) with the aim of evolving and analysing dynamical neural networks in agents acting in the environment [Nolfi & Floreano, 2000] (Chapter 4). In ER and related works in embodied cognitive science, researchers focus on

organism-environment interactions to obtain behaviourally fit agents. Traditionally the emphasis has been on the emergence of adaptive behaviour and cognitive processes [Clark, 1997][Chiel & Beer, 1997][Pfeifer & Scheier, 2001]. Unfortunately, as Ziemke *et al.* (2004, p. 340) note, the explicit investigation of cognitive processes distributed over organism *and* environment (distributed cognition) has received less attention. Distributed cognition implies cognition as 'smeared across' material environment and the dynamics of the whole coupled system that an agent uses to achieve behaviour [Hutchins, 1995] (see also [Clark, 2008]).

Because the aim of ER is the production of existence proofs [Harvey *et al.*, 2005, p. 84], it seems appropriate to use this methodology for studying the relation between the emergence of robust behaviour and distributed mechanisms. By requiring fewer assumptions than most other synthetic approaches [Izquierdo, 2008], ER also has the potential to address experimental discussions by understanding in dynamical terms the capacity for behavioural robustness that emerges at coupled system level. Even if these exact mechanisms are not observed in the biological realm, we will be developing conceptual and practical tools to guide theoreticians in the understanding of behavioural robustness in biological systems (see [Silverman & Ikegami, 2010] for experimental examples and [Weisberg, 2005] for related discussions rooted on perturbation analyses).

1.2 Thesis proposal

After the above discussions about brain-body-environment dynamics and distributed behavioural mechanisms, we now reintroduce the main direction of this work in more detail. The *purpose of this thesis* is to understand how minimal ER models can demonstrate robust behaviour. These minimal models are a computational tool to explore the simplest possible conditions for obtaining a feature of interest in evolved ER agents [Jakobi, 1998b][Harvey *et al.*, 2005]. ER experiments allow us to refute or defend our working hypotheses by demonstrating an existence proof for behavioural robustness given conditions we have supposed are necessary. In this respect, we attempt to introduce as few assumptions as possible about the nature of robust behaviour. The issue is that *there are not* direct studies about behavioural robustness in autonomous robotics and ER. This is also noted by Hubert *et al.* (2009): "Robustness has not been the center topic of research in robotics. Many studies mention robustness, but only as a property assigned to the system they present rather than as the main object of study. Unfortunately, no work has given a complete account of the robustness of their controller outside the realm of their own experience" (see also [Silverman & Ikegami, 2010]).

An agent in our experiments has an embedded brain-like control system (neurocontroller) evolving in a body. Agents exploit behavioural opportunities by using dynamically engaged features in different scenarios. We study how minimal, embodied, and situated ER agents (Chapter 3) sustain behaviours during interactions with the environment over an agent's lifetime. The behavioural control systems evolved are analysed for functional dependencies via coupled dynamics, which are required in the production of robust and adaptive behaviours in

our experiments. Dynamical systems theory (section 3.2.3) is employed as a mathematical tool to discuss how behaviours are exhibited. This and the central concepts for understanding robustness of behaviours (behavioural robustness forehand) are defined and explained in Chapter 2 and Chapter 3. Further motivation for each experimental study and some *lessons* are given in section 1.3 and 1.4 alongside a brief description of models, respectively.

The *main contribution of this thesis* is the methodological study of behavioural robustness in environmentally coupled ER agents, focusing on agents' distributed behavioural control (see section 2.5 for some observations from literature supporting this clain). Following current work in the ER field (section 4.1), we use non-linear neuron-like units and define a neural-network control system as agents' nervous system (brain). The network is structurally fixed in all of our experiments, but evolves in simulation for a particular body and environmental constraints (e.g. the presence of particular objects in the surrounding of agents triggering specific actions). Proceeding this way, we try to encourage the emergence of dynamical mechanisms in agent's body-environment systems while demonstrating robust and adaptive behaviour.

This thesis is exploratory, aimed largely at investigating robustness from a behavioural point of view, and our motivations are conceptual as well as practical. Our discussions in the rest of this thesis present evidence that behavioural robustness may be better defined in terms of coupled system dynamics, rather than only as the product of mechanisms *inside* agents.

1.3 Thesis organization

In order to introduce the reader to the wide scope of robustness research, we begin the thesis with an account of robustness as a property demonstrated through coupled dynamics. Figure 1.2 (based on Figure 1.1-C) shows a schematic representation of the chapters' organization. Each chapter provides details of the motivations, objectives, methods, implications, and consequences of the proposed investigation and associated discussions.

Chapter 2 presents a selection of the most representative works studying robustness from an organism-lifetime perspective. The chapter starts with a discussion of what it means when we say that biological and artificial agents are 'robust'. It is expected that by the end of Chapter 2, the reader will be able to understand the motivations that guide robustness research in biological and bio-inspired contexts. Chapter 2 includes some remarks based on our literature review (state of the art) and our distributed account of robustness in section 2.4. However, this chapter does not explain the main conceptual frameworks used as the basis of our discussions in experimental chapters. That is the goal of the following chapter.

Chapter 3 discusses some aspects of the main conceptual framework used in this thesis: embodied, situated, and dynamical systems. A brief description of distributed cognition is also given with emphasis on ER field. Several examples of related work from the literature are introduced.

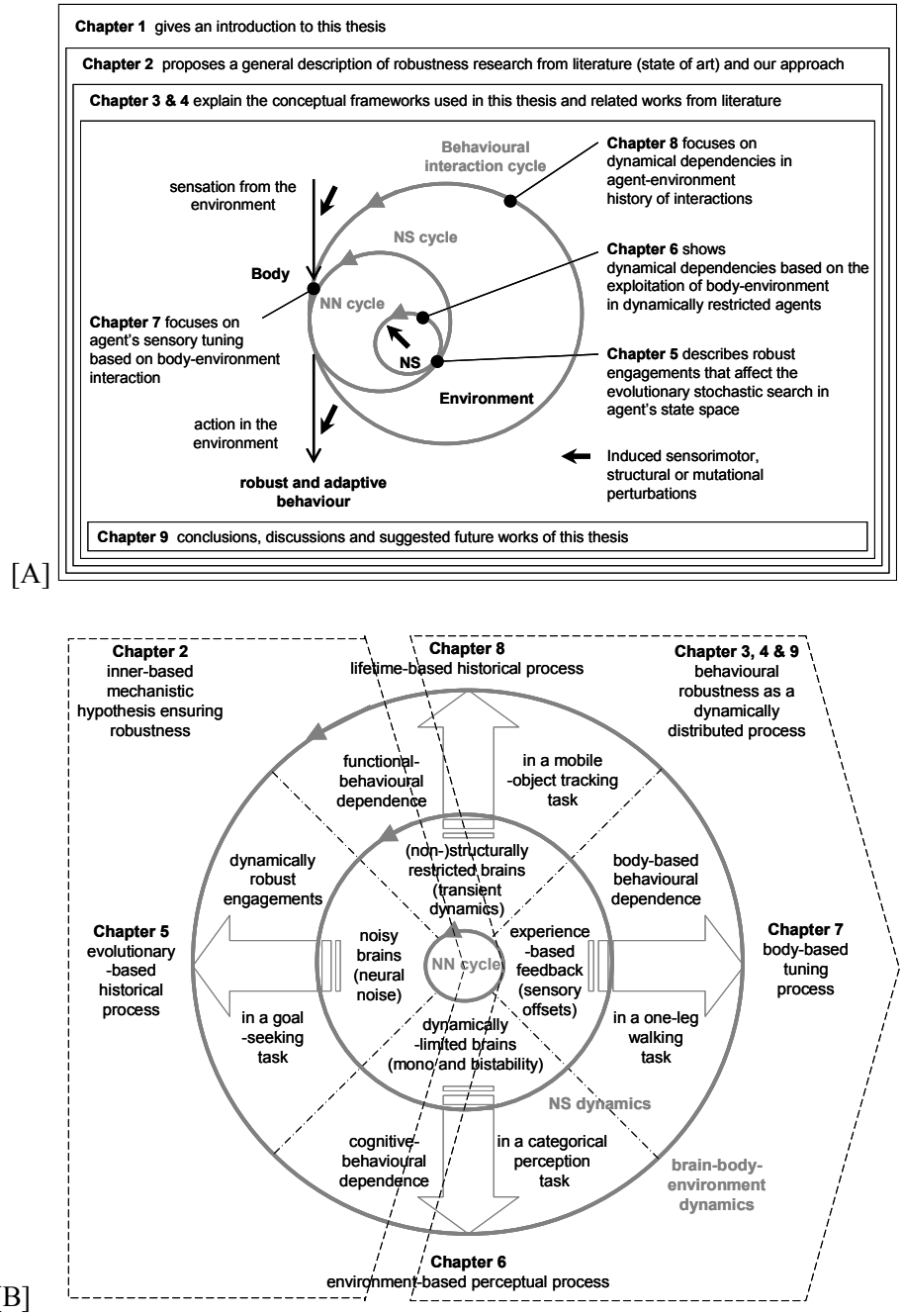

Figure 1.2 – Schematic representation of the chapters' organization in this thesis to study the emergence of robust behaviours in embodied, situated, and dynamical agents. [A] Black dots represent the place where the experimental study applies analysing certain aspects of the coupled dynamical system. In general, experimental chapters discus the dynamical interactions between nervous system (NS) through an associated neural network (NN), the body of an agent, and the environment We analyse the system as different dynamical loops that contribute to robust behaviour despite internal malfunctions and external perturbations (thick arrows). [B] Plot relating descriptions of the implemented model-agent in each experimental chapter (outer labels) and dependencies of agents to brain-body environmental factors (intermediate labels). Inner labels specify induced dynamics or structural features at neurocontroller level. Plot [B] also represents the transition that this thesis wants to highlight from robustness promoted by the internal structure of agents to a dynamical phenomenon involving inner controls, body, and environment.

Chapter 4 explains the main features of ER for evolving minimal models. A brief account of genetic algorithms and neural networks are also presented. This chapter serves to introduce experimental methodologies across the ER field.

The following chapters show results from four experimental scenarios analysing the behaviour of sets of agents and the best-evolved ones using dynamical systems theory (section 3.2.3). In most of the experiments, we discuss the ability of agents to maintain or flexibly switch between behaviours that a particular task requires. Most of the experimental evidence has been published in international journals and conference proceedings, or is under review (see Preface of this thesis). These articles are similar to associated experimental chapters but reduced in content.

Chapter 5 gives an initial discussion as to what agents develop robustness 'against.' Using an evolutionary search of parameter space [Jakobi, 1998b], this chapter proposes that the presence of certain level of noise in the activities of neurons (neurocontroller level) leads to further behavioural robustness during agents' lifetimes. Results are compared in a goal seeking (phototaxis) task between high noise, medium, low and noiseless situations. Behavioural analyses show that robustness emerges from coupled brain, body, and environment interactions via evolution in best-evolved agents. In dynamical terms, results also suggest that behaviourally robust agents require internal dynamics that are resistant to non-functional bifurcation under neural noise perturbations. The discussion emphasizes the role of dynamical engagement in combination with internal-control dynamics in the production of robust behaviours. Chapter 5 is based on work published in [Fernandez-Leon & Di Paolo, 2007, 2008].

Chapter 6 proposes experiments that help to understand both 'in which way' agents use their situated condition to exhibit expected behaviours, and 'how' perturbations affect the production of a minimal cognitive task (categorical perception). We evolve agents that demonstrate basic internal dynamics, namely mono- and bistability [Strogatz, 1994], when they do not receive stimuli from the environment. More explicitly, the proposed analyses show that studied neurocontrollers are globally stable around one fix-point (monostable) or reveal the presence of two fixed-point attractors (bistable) within the intrinsic dynamics of analysed successful agents. The model requires that agents, despite their limited internal dynamics (one or two internal states), exploit opportunities from brain, body, and environment to accomplish the task. We observe a slight but significant tendency toward better task performance in the presence of sensorimotor, structural, and mutational perturbations in monostable agents. This is made in comparison to bistable agents with less environmental dependence. Chapter 6 emphasizes the role of agent situatedness in the production of robust behaviours contrasting the intuitive feeling that an agent with more internal states would be more 'sophisticated' and more adaptive than a dynamically simpler agent. More sophisticated in the sense that a bistable agent could exhibit different behaviours and it could 'switch' between internal states due to the effects of perturbations and external changes.

Previous chapters research on the use of model features, internal agent dynamics, and situatedness for the exhibition of robust behaviours. In Chapter 7 we investigate the role of

agent experiences in shaping or tuning the sensory mechanisms used to generate behaviour. The emergence of dynamical engagements for a one-legged walking task is investigated in the presence of high and medium noise perturbations, and a noiseless situation. The tuning of incoming signals is implemented through the evolution of 'sensory offsets' (further explained in Chapter 7). Results indicate a positive relation between robust behaviour in more complex environments in the face of sensory noise and the capacity of agents to fine-tune signals via multiple sensory offsets. However, having multiple sensory offsets is not always beneficial for behavioural robustness; it depends on the complexity of incoming signals: the more complex the incoming sensing is, the more convenient the use of multiple sensory offsets is for one-leg walking behaviour.

Chapter 8 explores the role of an agent's history of interactions with the environment in generating robust behaviour. When using a model that is primarily governed by the history of agent-environment interactions (mobile object-tracking task), we show that not all types of dynamical dependence between brain, body, and environment lead to behavioural robustness. Analyses indicate that perturbations of behavioural mechanisms can be (i) detrimental, if they are mostly grounded on factors that are necessary for the behaviour, or (ii) beneficial, if they are mainly based on factors that are sufficient for the behaviour. Examples of these factors are detailed in section 8.3.3.

The thesis concludes in Chapter 9 suggesting that the ability of environmentally coupled agents to behave robustly can be seen as rooted in distributed control mechanisms based on coupled functional dependencies of the nervous system (brain), body, and environmental dynamics, and cannot be solely attributed to mechanisms in an agent's *internal* environment (i.e. agent neurocontroller).

1.4 Summary of contributions

This section summarises the main achievements of this work (see also section 2.5 for further remarks in relation to our literature review). This thesis demonstrates that adding a certain level of noise to neural activities increases the chances that evolutionary search will find robust agents; i.e. behavioural robustness to most neural and sensorimotor perturbations in the face of noisy signals. We show that neural networks with noisy neurons can be evolved to control agents that robustly perform an expected task (goal approaching). Agents with these controllers use dynamical coupling to achieve robust behaviour. Results suggest that evolution implicitly selects neural systems that are noise-resistant during coupling behaviour by concentrating search in regions of the state landscape far from non-functional bifurcations. That is, the effects of perturbations at neurocontroller level do not seriously affect the production of behaviours because neurocontroller's dynamics remain most of the time functional allowing the agent still to perform goal approaching by using its environmental coupling. We provide an asymptotic explanation for how fitness is maintained high despite neural noise, where those controllers evolved with enough noise undergo fewer long-term dysfunctional bifurcations because of noise.

This thesis proposes that it is not appropriate to assume a capacity for behavioural robustness derived from the internal dynamical limitations of situated agents. We provide two examples of dynamically limited neurocontrollers (i.e. having one or two internal states) in order to support this claim. Agents with these controllers exhibit minimally cognitive behaviours that demand some state by exploiting their inner dynamics coupled with one of two different types of objects in the environment. We provide analysis where agents showing further cognitive-behavioural dependency to their environments obtain a small but significant tendency toward better fitness under most sensorimotor, structural, and mutational perturbations. This observation again reinforces the idea that behavioural robustness *cannot* be deduced directly from internal structure itself, a common belief in literature; rather it must be observed in the context of coupled dynamics arising from the brain-body-environment.

This thesis shows that agents with the capacity to make their own stimuli (i.e. finding their own 'reference' in how to process body signals based on agent-environment history of interactions) do not necessarily develop fully internal control in a task that requires repetitive body movements in the environment. We show that behavioural control can also emerge from periodic sensory stimuli from agent bodies. Furthermore, after bifurcation analyses, we realize that the coupled dynamics allow neurocontrollers to work far from non-functional bifurcations (i.e. no walking behaviour). This behavioural control emerges as a combination between neurocontroller attractor landscape, body, and environment couplings.

Finally, this thesis experimentally demonstrates that successfully evolved agents can use a combination of both internal dynamics and their history of interaction with the environment to exhibit robust, yet adaptive coupled behaviour. We show that successfully evolved agents can emerge with at least two different modes of exhibiting behaviour, one in which inner controls necessarily depend on a set of specific environmental factors (i.e. the presence of a responsive agent), and another for which these factors are equally sufficient for behaviours (i.e. a responsive 'or' non-responsive agent). We show that the first mode is more vulnerable to perturbations on that set, suggesting that robust agents will exploit behavioural opportunities rooted in external factors when available. We provide another concrete example of how behavioural robustness is a capacity of the coupled agent-environment system, rather than warranted exclusively by agents' internal mechanisms.

Chapter 2

Systemic robustness: concepts and insights from Systems Biology

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"It should be noted that from now on 'the system' means not the nervous system but the whole complex of the organism and the environment. Thus, if it should be shown that 'the system' has some property, it must not be assumed that this property is attributed to the nervous system: it belongs to the whole; and detailed examination may be necessary to ascertain the contributions of the separate parts."

W. Ross Ashby, 1960

This chapter is a comprehensive overview of the motivation of our study mainly from a systems biology perspective. It divides into two main parts: a survey of the state of art on robustness (from section 2.1 to section 2.3) and our relatively novel approach to robustness research (section 2.4). We contextualize current studies as background for understanding systemic robustness with the focus on essential aspects of such phenomenon in biological systems. Our survey shows that most of previous approaches examine isolated parts of an organism in order to explain robust traits, rather than promoting a holistic understanding, an emerging tendency in current systems biology [Kitano, 2002]. This chapter emphasizes instead on the coupled dynamical nature of robustness and extracts from prior work the arguments that support it. Work here also introduces discussions from two different perspectives: robustness during organism evolution and robustness over organism lifetime. We mainly focus this chapter on the latter idea, however.

We begin with a summary of attempts to address robustness from systems biology with emphasis in neurosciences. An initial mapping of the basic concepts of robustness into the language of dynamical systems is introduced and associated literature underpinning this work is described (from section 2.1 to section 2.3). In section 2.4 we introduce *our definition of robustness*

in order to use the term consistently throughout. Section 2.4.1 describes our approach to understand behavioural robustness and provides some focused discussion around open questions. We remark on important points in this chapter in section 2.5 and section 2.6. These foundations are given below.

2.1 Approaches to robustness

Understanding the origin of some behavioural properties such as robustness and adaptivity in biological organisms is a delicate task [Ashby, 1960, 1958b]. It is relatively easy to produce simple artificial organisms exhibiting particular behaviour, but identifying similar processes in living organisms is not generally trivial, as been observed with cognitive processes [Beer, 2000, 2004a, 2004b, 2008]. In fact, Di Paolo's (2009) discussion implies that cognition is a relational phenomenon of brain, body, and environment, and thereby is *not localizable* (see [Ashby, 1960, p. 70]). Another difficulty arises in that the number of concurrent behavioural processes in most biological organisms is usually considerably higher than those in artificial systems. For instance, complex visual sensory information and body signals from different organs in a mammal are combined to produce motion movements; whereas in artificial agents simple configurations like sensor-motor connections can show similar behaviours as discussed in [Braitemberg, 1986].

The problem of how biological organisms exhibit normal behaviours in the presence of perturbations has much room for new ideas. Von Neumann (1956) noted the complexity of such a problem by opening debates on 'the synthesis of reliable organisms from unreliable components'. Reliability in this context refers to the ability of artificial or biological organisms to maintain its capacities (*functionalities*) in normal situation, as well as under unexpected internal or external factors (see [Ashby, 1960] and [Stebbing, 2009]). Factors like these generally are referred in literature as 'perturbations' to systems' functionalities [Kitano, 2004a]. Since that time, questions have been raised about how biological organisms and comparable artificial agents (like mobile robots) can deal with component failures in robust ways.

Discussions about the nature of robustness have largely focused on stability [Jen, 2003] and robust design [Jen, 2005]. For example, since Harry Nyquist (1932) provided the first two measures of robustness (gain margin and phase margin), while working at Bell Telephone Laboratories, robustness has been an increasing topic of interest also from an artificial viewpoint [Cogan, 2006]. In closed-loop control systems [Healey, 1975], phase margin indicates relative stability − the tendency to oscillate during damped response to an input change. Gain margin refers to absolute stability and the degree to which the system will oscillate without limit given any disturbance [Horowitz & Hill, 1989]. Von Neumann (1951, 1956, 1966) in addition started discussions about robustness, among other issues, related to the problem of self-replicating systems. His notion of 'one robot building another robot' is known as the von Neumann's kinematic model of self-reproduction. As he developed this design, von Neumann came to realize the difficulty of modelling realistic robots. However, his idea of a universal constructor has never been subject to physical implementation [Friedman, 1996] because the fragility of the modelled

mechanisms against unavoidable perturbations was drastic in more natural kinematic settings: "[A] universal constructor should be robust *per se*, […]. Thus, the system should be able to deal with more or less continuous physical entities that inevitably involve fluctuations and uncertainty. In such settings, the system itself is responsible for the robustness of its workings." [Sayama, 1996, p. 2]. This example illustrates the interest in the study of robustness in robots from an internal-mechanism-based standpoint.

Biological organisms and robots are similar in that they both may be placed under conditions requiring robust behaviours. The main difference between these types of systems is that in the former case designers impose internal and external requirements that robots must obey (e.g. the generation of moving home actions when the level of robots' batteries are low). Organisms instead are guided mostly by what their metabolism dictates (in [Boden, 1999] it is discussed this last point further). Metabolic (internal) requirements usually help to contextualize the emergence of actions in the environment that biological organisms exhibit to remain themselves alive. Homeostasis, as an example of an internal requirement in biological organisms, indicates a specific way that an inner state can vary, but the state in the end remains relatively constant and must be maintained. Cannon (1939) proposed the concept of homeostasis as organisms' self-regulating mechanisms that enable the organism to preserve essential physiological variables (e.g., body temperature) in a state of dynamic balance. Note, on the other hand, that homeostasis only maintains a *physiological state* and not necessarily full systemic functionality [Kitano, 2004a]. The continuation of organism functionality implies an *active and flexible* control in the presence of perturbations [Kitano, 2004a, 2007]. Despite current insights on this matter, it is still under debate how to approach to robustness from an artificial context and in the natural realm (see [Hubert *et al.*, 2009] and [Silverman & Ikegami, 2010] for a bio-inspired perspective, and [Weisberg, 2005] from a perturbation analysis approach).

Section 2.1.2 discusses how to research on robustness with some detail after we introduce a clarification about 'what a system is' in the next section.

2.1.1 A brief explanation of the notion of system

Different, but connected definitions of 'system' appear in General Systems Theory [von Bertalanffy, 1968] and Cybernetics [Ashby, 1956]. To exemplify, a system is:

> "[…] a set of interacting or interdependent parts forming an integrated whole" [von Bertalanffy, 1968].

> "[...] any set of variables that (the observer or experimenter) selects from those available on the real machine" [Ashby, 1960, p. 16].

The last definition suggests an important feature of 'what a system is', where it emphasizes the role of the observer or experimenter, who is supposed to select the variables and whose

intervention implies that any system is a mere abstraction. Despite differences in definitions, systems in general share some common characteristics [von Bertalanffy, 1968], including:

- systems have *structure*, defined by parts and their composition;
- systems exhibit *behaviour*, which involves inputs, processing, and outputs of information;
- systems have *interconnectivity*, where the various parts have functional as well as structural relationships between each other.

In the context that we want to focus this thesis (i.e. the interaction of an organism or agent with the environment), we can ask whether it is reasonable to assume than the environment is part of the system under study, or if it represents another part that only influences the organism's decisions as a system (Figure 2.1). If one assumes the environment as the entire universe minus the agent, we presume that the system under study is the organism, ignoring the rest [Beer, 1997]. For example, as Beer (1997, p. 264) exemplifies: "[…] out of the blue, a door could suddenly open, and a complete stranger could walk into the door. Therefore, for purists, we can extend our model of the environment as a dynamical system with additional time varying inputs that model this nonlawful behaviour." His example suggests that focusing on agents' internal structures (as a system) does not necessarily involve the outside environment (i.e. the dynamics that affect agent local environment).

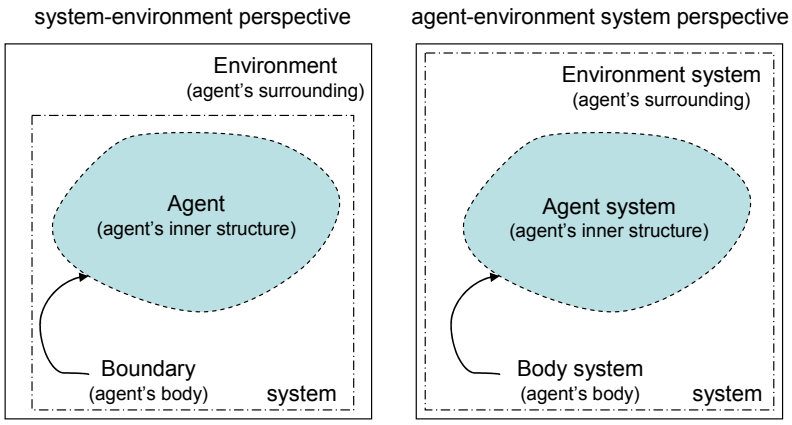


Figure 2.1 – Schematic representation of a closed system and its boundary. [A] The agent-based idealization of a system, and [B] the agent-environment system perspective. Dotted-line squares represent two different notions of system, which this work uses to address discussions. The [B] approach is mainly concerned with this thesis. Plots based on interpretations from [Beer, 1997], [Chiel & Beer, 1997], and [von Bertalanffy, 1968].

The internal structure of an agent, its body, and its environment can be a rich, complicated, highly structured coupled dynamical system, and behaviour emerges from the interactions of all three systems [Beer, 1997] (Figure 2.1-B). This understanding of 'brain-body-environment system' certainly makes dynamical analysis complete, yet more complicated because the agent-environment coupling is non-autonomous. In this thesis, we follow Beer's philosophy defining a system under study as agent *and* environment (*agent-environment system*), discriminating *inner-system* when necessary to refer to agent internal features (Figure 2.1).

2.1.2 Systemic robustness: how to approach it?

Definitions of robustness have been a primary topic of discussion in biological and engineering fields (see [Jen, 2003], [Calcott, 2010], and [Lesne, 2008] for related discussions). In a metabolic context, the concept of robustness is associated with limited phenotypic variation across large changes in kinetic parameters [Hurst & Randerson, 2000][Westerhoff *et al.*, 1984]. In cell biology, robustness is used in one sense to describe cell fate decisions remaining constant while transcription regulation is stochastic [Kepler & Elston, 2001]. These examples hardly connect each other. Krakauer (2005, p. 186) also proposes that:

> "Robustness relates to two critical properties of complex biosystems: the long-term limits to evolutionary change and the short-term persistence of system function. Put differently, robustness mechanisms are one of the bridges connecting the dynamics of ontogeny with the dynamics of phylogeny by limiting phenotypic variation and also providing some means of exploring alternative genotypes without compromising the phenotype."

Despite the context dependence of his observation, Krakauer (2005) suggests an important distinction that we wish to emphasize in this section: *genotypic* and *environmental* (lifetime) robustness. In the former, perturbations (e.g. gene mutations) are inherited [de Visser *et al.*, 2003], whereas in the latter case (e.g. environmental change) they are not [Hagen & Hammerstein, 2005]. In particular, environmental robustness (i.e. the maintenance of functionality despite perturbations from the environment) can be achieved through mechanisms that emerge from organisms' evolution acting over agent lifetime. An example is phenotypic plasticity [Krakauer, 2005] — ability of an organism to change its phenotype in response to changes in the environment [Price *et al.*, 2003]. Robustness therefore can be defined in terms of interactions between an organism and its environment.

Krakauer and Plotkin (2005) have also described three principles though which we can understand the evolutionary response to mutations in robust systems: the principle of canalization, the principle of neutrality, and the principle of redundancy. They extend the discrimination of principles to include feedback, modularity, spatial compartmentalization, distributed processing, and the extended phenotype. Other authors further consider *degeneracy* [Fernandez & Solé, 2004]

and *distributed robustness* [Wagner, 2005] as promoters of robustness. For an extensive discussion of genotypic robustness based on evolution see [Wagner, 2007] and for further descriptions of robust principles see [Krakauer, 2005] and [Kitano, 2004a]. Our brief account of principles and structural properties of robust systems at organism level suggests an intrinsic value to exploring and understanding biological features: it will provide insights into overall rules that both simple and highly complex (evolvable) systems follow [Kitano, 2002].

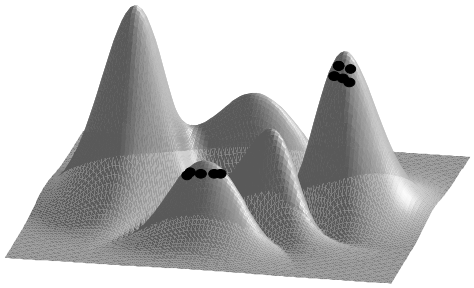
Scientific fields like systems biology ground research on mathematical simulation of biological systems to clarify some complex aspects and hypothesized foundations of robust systems. From a biological context, the systems biology approach integrates well with adaptive systems theory, since the former is an inter-disciplinary study that focuses on holistic interactions, as opposed to reductionism. According to Kitano (2007), the exploration and the study of particular systems through theoretical and mathematical models have the potential to define general properties of biological robustness. Such an approach also has an impact on the design of artificial systems with robust properties. In this respect, again, the study of specific instances of dynamical systems shaped by structural, environmental, and evolutionary constraints can help us to discover the conceptual basis of robustness (see [Alon, 2006] and [Kitano, 2004b] for examples of studies in the systems biology field).

Summarising the above perspectives, most researchers in robustness accept a phenomenological taxonomy of internal and structural features observed in natural organisms that support robust organization (e.g. redundancy, feedback, modularity, spatial compartmentalization, distributed processing, control systems, decoupling, and the extended phenotype). A new tendency in robustness research aims to uncover mechanisms promoting the persistence of functionality, both from an organism-based point of view. Case studies in literature normally illustrate the ubiquity of specialized robustness mechanisms in biological systems. However, robustness as a concept makes sense in each context only if we precisely define and localize the phenomenon under study. The following section focuses with some detail on the differentiation of robustness (genotypic and non-genotypic) that we have introduced in this sections.

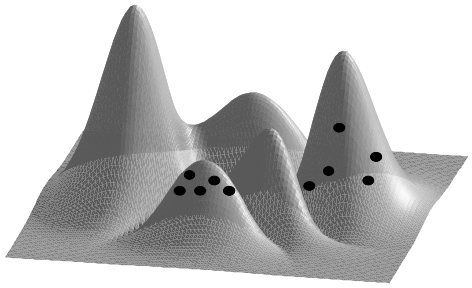
2.1.3 Genetic vs. non-genetic mechanisms for robustness

We can use different approaches to understand robustness in one particular system. For example, one approach can be emphasized dividing a system into parts, guiding division on functional requirements (what a system is supposed to *do*). A division based on non-functional requirements might define, by contrast, how a system is supposed to *be*. To exemplify, the second perspective can approach the phenomenon of robustness by understanding the statistical effects of genes in fitness and the role of genes during organism lifetime. Both the division by functional and non-functional criterion provides important perspectives that usually complete each other in the study of exhibited robust traits [Wagner, 2007][Krakauer, 2005] (see also [Hansen, 2006]). However, the common point shared by both approaches is that mostly the study of lifetime robustness addresses a number of interesting and important properties of biological systems that are widely

recognized as robust [Kitano, 2006, p. 133] (e.g. behavioural robustness during organism lifetime).



[A]



[B]

Figure 2.2 – Schematic representation of a landscape characterised by peaks of high fitness (*z*-axis) but low robustness, and other ones of low fitness with high neutrality (robustness) The *x* and *y* axes represent sequence space. The coloured dark grey surface is the fitness plane. Black dots stand for solutions in the fitness surface. Plots show [A] the control case and [B] the situation after increasing in mutation rate on solutions (e.g. genotypes). Plots arbitrarily represent the size and shape of the dark grey fitness surfaces and are presented solely for illustration. Figures adapted from [Burch & Chao, 2000].

Most of this thesis focuses on lifetime robustness concentrating on the whole organism-environment dynamics, rather than focusing on functional divisions of isolated parts and their dynamics. This decision avoids drawbacks of studying robustness at the evolutionary level, since during evolution the coupled interactions of agents with their environments are difficult to explore. Let us to exemplify this point by giving an example from the genetic context: suppose that we have found two different control strategies after evolution in two different organisms (phenotypes) from the same population. We discover that both phenotypes show quantitatively similar fitness under the same experimental circumstance. After inducing mutational changes

(variations in their genes), we measure a decrease in fitness in one of them, which indicates less resilience to these variations. The way that the negatively affected phenotype behaves suggests a decrease in fitness in response to the same amount of mutation than the phenotype exhibiting no decay in fitness. Following Burch and Chao (2000) arguments, we can indicate that such differentiation in fitness is caused by variations in where the mutated phenotype is placed in the multidimensional fitness landscape. The phenotypes showing decay in performance after inducing mutation are in fitness peaks (Figure 2.2). The phenotype showing no decay of fitness will be in a flatter region of the fitness surface with relatively equal fitness to its non-mutated genotypic expression. A phenotypic expression of the non-affected genotype therefore is more robust with respect to induced mutations than the another phenotype because a mutational change will not produce significant changes in fitness [Wilke *et al.*, 2001][Elena & Sanjuán, 2003](see also [Wilke & Adami, 2003]). Our example shows an implicit association between the emergence of robustness during the evolutionary phase and robustness during lifetime based on fitness. In fact,

> "Robustness is the fundamental organising principle of evolving dynamic systems such as biological systems. One could say that robustness allows evolution to happen and that evolution favours robustness." [Cogan, 2006, p. 20] (from a general biological context).

> "Dating back to at least Waddington, it has been suggested that mutational robustness may be related to the requirement to withstand environmental or stochastic perturbations. […] This means that selection during evolution for environmental or stochastic robustness (also referred to as canalization) may frequently have the side effect of increasing genetic robustness. A dynamic environment may therefore promote the evolution of phenotypic complexity […]." [Lehner, 2010] (from a molecular biology context).

Although the study of robustness during evolution is insightful in many respects, the goal of this thesis is to discover mechanisms for behavioural robustness that emerge from evolutionary processes by means of Darwinian selection and are exhibited during agent lifetime, rather than in evolutionary aspects of agents with robust capacities.

2.2 Maintenance of lifetime functionality in systems

It is well known that biological organisms use adaptive actions as a way to maintain functionality after component failures. Adaptivity is frequently attributed to the capacity of an organism to regulate itself within the boundaries of its own internally defined properties [Di Paolo, 2005, p. 429]. In this respect, not only internal adaptation can take place, but also *adaptive behaviour*. Ashby gives a mechanistic definition: "behaviour is adaptive if it maintains the essential variables within physiological limits" [Ashby, 1960, p. 58] (see also [Umpleby, 2009]). This capacity is

commonly discussed in the context of the nervous system co-developing with body and the dynamics of the environment [Chiel & Beer, 1997][Gallagher, 2005].

The established theory of adaptive systems tells us that biological organisms typically (but not exclusively) reorganize their components and in doing so remain functional to perturbations [Ashby, 1940, 1960]. We extend this observation further in Chapter 3. Kitano also indicates the importance of studying the dynamics of agent-internal-systems and properties in order to understand biological systems in presence of perturbations:

> "To understand biology at the system level, we must examine the structure and dynamics of cellular and organismal function, rather than the characteristics of isolated parts of a cell or organism. Properties of systems, such as robustness, emerge as central issues, and understanding these properties may have an impact on the future of medicine. […]" [Kitano, 2002, p. 1692].

Failures of adaptivity can produce inconveniences such as the exhaustion of adaptive resources, malfunction of regulation, loss of adaptive buffering provoking the activation of extreme regulation, and disharmonious activation of conflicting adaptive mechanisms [Di Paolo, 2005]. Failures can result from internal malfunctions or by externally induced perturbations. Malfunctions occur, for example, when sensory systems in a biological organism do not work properly due to aging, or when an organism is acting in situations that it is not 'habituated' to deal with. The phenomenon of habituation is regularly discussed in animal behaviour: "if an animal is subjected to repeated stimuli, the response evoked tends to diminish. The change has been considered by some of the simplest form of learning" [Ashby, 1960, p. 189]. What Ashby's observation suggests is that perturbations are relative to organism knowledge.

In terms of dynamic systems theory (section 3.2.3), a major factor underlying an intuitive notion of robustness is *structural stability*. "A dynamical system is said to be structurally stable if small perturbations to the system result in a new dynamical system with qualitatively the same dynamics" [Jen, 2003, p. 2]. Small perturbations can be seen in this context as external parameters of the system. Given a system, a variable not included in it is a parameter, where the word 'variable' is reserved for a factor modelled *within* the system [Ashby, 1960, p. 71]. To give an example: assuming that the flow of water in a river only *externally depends* on a wind speed, the flow is structurally stable to wind speed variations if small changes in wind speed do not qualitatively modify the dynamics of the flow by producing a new structure such as an eddy [Jen, 2003][Diacu & Holmes, 1996]. In non-biological adaptive systems like a river, this example shows us that there are different responses of a system, which depend on the magnitude of changes of external dependencies.

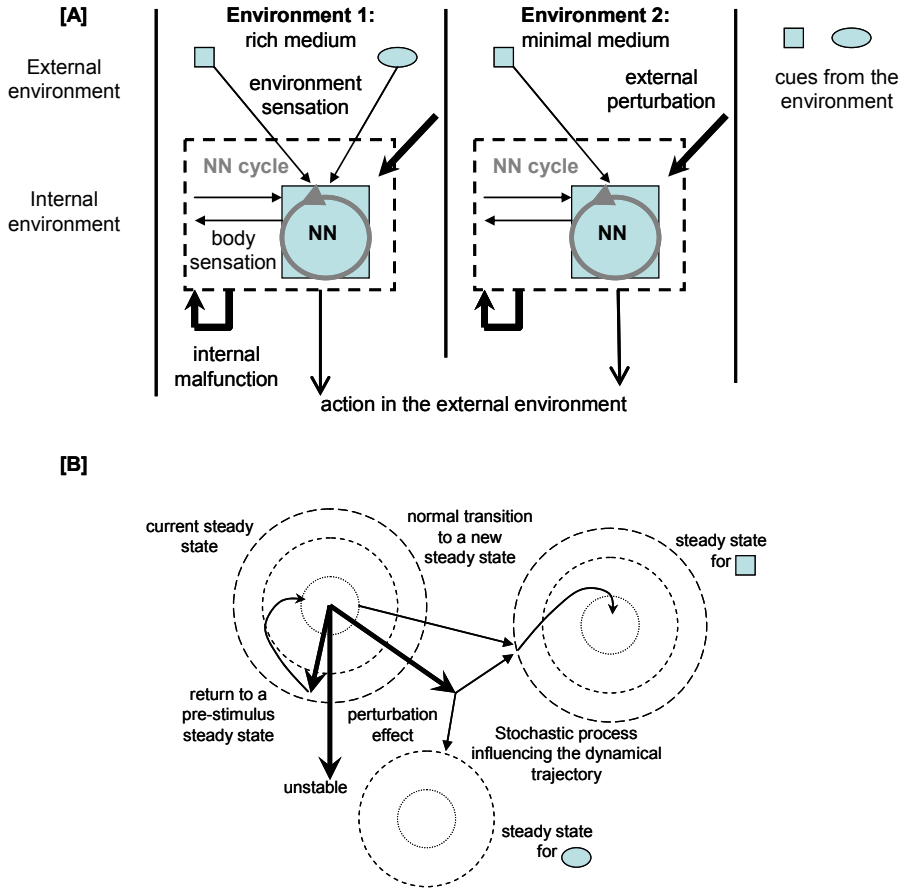


Figure 2.3 – Illustration of environmental influences and the effect of perturbations on inner dynamics. In [A], two environments are shown (rich and minimal mediums). The agent-internal-system selects cues available in the environment (via the body sensing) and responds with actions in the environment. Cues are information inputs to inner-control and are deemed essential to accomplish actions. NN represents a neural network. Plot adapted and extended from [Freilich *et al.*, 2010]. In [B], this plot represents that a current state of an internal control can be modified by small or big perturbations pushing the agent-internal dynamics within the current boundary of attraction or far from it. Perturbations may produce a dynamical return to pre-perturbation state, dynamical changes toward different steady states, or push current dynamics toward an unstable region (from which the dynamics will eventually return if possible). When an organism with such dynamics remains functional despite perturbations, the changes of regions can be part of the robust response needed to reach stability. Plot adapted from [Kitano, 2004a, 2007].

In dynamical systems theory, three common outcomes arise from perturbations in structurally stable systems [Kitano, 2007, p. 137] (Figure 2.3):

1. The system *cannot* tolerate perturbations and it is no longer functional — in the sense that it is not able to sustain the 'same' defined functionality;
2. The system *compensates* for effects of perturbations and *maintains* a specific steady state;

3. The system *changes* (or it is pushed by perturbations) to another stable region in the state space (if any exist) that is also functional. This last outcome commonly implies multi-stability to radical changes in the face of perturbations [Ashby, 1960, p. 209][Anderson, 2002].

These outcomes indicate that robustness, as a capacity of biological organisms, does not necessarily only imply maintenance of a dynamical state (toleration) to malfunctions and internal or external perturbations. For instance[1], imagine two organisms moving from A to B (two distant points in the physical space) while a predator is trying to catch them. The first organism, which depends extensively on internal state variables, will typically move in a predictable path for which will be cached and killed. A second organism dodges from left to right in response to incoming signals based on the movements of the predator, and may be is more likely to survive. It is worth noting that during environmental coupling not only can an organism rely on internal control for robust behaviour, but also on body features[2]; for instance, insects such as moths and butterflies can fly pseudo-randomly, and thus hinder predation due to wing design and the interaction with the environment. This simple example suggests that organisms remain functional by producing changes at the internal (i.e. based in flexible sensorimotor control) and environmental level (e.g. behavioural escaping movements). Tolerance to perturbations is defined by the organism organization and environmental current state [Di Paolo, 2005][Ashby, 1960, p. 61].

2.2.1 State dependency in robust systems

As we introduce in the previous section 2.2, internal and external factors as can be seen as part of the mechanisms that triggers the exhibition of behaviours. Figure 2.3 indicates that factors like these influence state where an inner-control converges during lifetime. In fact, Kitano (2007, p. 1) goes further saying that the cooperative work of components in an internal system such as brain and nerves is what enables the maintenance of functional requirements during organism interaction with the environment. More specifically, he says that:

> "The coordinated physiological processes which maintain most of the steady states in the organism […] involving, as they may, the brain and nerves, […], all working cooperatively […]."

Taking an integrative perspective of agent-environment coupling, we hypothesize a corrective tendency of agent-internal-control can be induced by dependency on internal and external events which are essential to organisms' functionalities in some environments but not in others (Figure 2.3-A) (see also [Freilich *et al.*, 2010]). These dependencies can direct inner-agent's dynamics to

[1] Dr. Inman Harvey suggested this example in a private communication.

[2] Dr. Andrew Philippides indicated this observation.

functional states, much the way a finite-state machine conditionally transitions based on input. However, even if an organism has evolved to accommodate itself to a set of steady states given specific environmental conditions, the organism's internal system can be driven toward a 'wrong-state' by the effects of unexpected perturbations (Figure 2.3-B). One could then ask: *what kind of features may be found in simple agent-internal-systems exhibiting a tendency toward correct states despite perturbations?*

Rigorous answers to this question are rare in current literature of neuroscience and cognitive science fields (see [Beer, 2004a] for discussions in a cognitive context). Whereas an organism's internal dynamics may be the prime mechanism for handling certain types of perturbations, in the presence of radical environmental changes biological organisms can also use coupled body-environment dynamics to mitigate the effect of perturbations. For example, most desert animals avoid being out in the sun during the hottest part of the day by looking for refuge, and desert mammals, reptiles and amphibians live in burrows to escape the intense desert heat. Rodents also plug the entrance of their burrows to keep the hot and dry desert winds out. These examples suggest adapted actions and for such the named animals exhibit robust behaviours to sun heat.

Studies in neuroscience and systems biology generally research organism-centred accounts of robustness as we previously discussed (Figure 1.1-A). Again, this partition is not always helpful for thinking of systems as 'highly-interdependent' because it focuses on one-third of the potential behavioural interactions. As an example of this last point (the 'bad' approach), neural network models have been used to explore how modularity can lead to more efficient task management [Calabretta *et al.* 1998]. Despite recognized robust properties of most modular neural networks to noisy data [Arbib, 1995], a considerably high amount of noise still drastically reduces their filtering capacity. In fact, internal properties like modularity, decoupling, and redundancy are conventionally thought to be necessary for (behavioural) robustness as indicated in Chapter 1. Properties like these may be required to support functionality to certain perturbations between control systems and body, but they do *not* in themselves ensure robust traits, as reported in the literature (see [Kitano, 2004a, 2007][Krakauer, 2005] for complementary discussions).

2.2.2 Dynamics enhancing robustness against perturbations

One of the most influential works in theoretical biology was proposed by Kitano in 2004a, and extended in [Kitano, 2007]. He emphasizes the necessity for a conceptual framework to understand biological robustness at organism level (see [Wagner, 2007] for a complementary approach in terms of evolution). Kitano (2004a) has discussed robustness mostly using tools from dynamical system theory indicating that: "robustness is a systemic property of some dynamic systems with appropriate functional organizations." Another example is:

> "[…] system controls, modularity, alternative mechanisms and decoupling serve as basic mechanisms to provide robustness to the system, but these mechanisms need to be organized into coherent architecture to be effective at the level of the

> organism. Enhancement of robustness against perturbations […] require[s] proper dynamics. Therefore, evolution of organisms can be viewed, at least in one aspect, as evolution of control systems." [Kitano, 2007, p. 835] (from a systems biology context).

Kitano's conception of internal mechanisms sustaining behaviour necessarily requires external stimuli that perturb a current organism's state. Without a dynamical explanation of the emergence of agent-internal-mechanisms, however, it is hard to understand how control emerges at inner-level (e.g. nervous system) and in relation to body, and environment dynamics. We also believe that any interpretation of robustness must be defined in terms of structural features and explained using dynamic systems theory. This observation is also supported by the following quotation in the sense that a dynamical understanding of robust traits is required:

> "We think that the intersection of the mechanisms responsible for persistent activity of single neurons with the activity of a network with local or nonlocal recurrence provides robustness against noise and perturbations […]." [Rabinovich *et al.*, 2006, p. 1237] (from a neurocientific context).

Despite efforts to understand the dynamics of biological organisms, their evolution, and their resistance to certain perturbations, internal dynamics are still considered as essential for robust traits. Quoting Kitano (2007, p. 835), "[…] system control is the prime mechanism for coping with environmental perturbations that require proper dynamics." Once more, the notion of *distributed mechanisms* in the brain-body-environment that exhibit robustness to certain perturbations, however, has not been seriously investigated in literature despite its recognized importance:

> "Distributed robustness, is […] poorly understood. It emerges from the distributed nature of many biological systems, where many (and different) parts contribute to system functions." [Wagner, 2005, p. 176] (from a genetic context).

> "[…] as found in biological systems, we can see that the origins of robustness against the failure of a given element are largely associated with a distributed mechanism of network organization." [Macía & Solé, 2008] (from a synthetic cell context).

These claims, while interesting, still view robustness as localized and distributed only intra-organism in the form of a network organization, rather than distributed in the whole agent-environment system. The following section further discusses the idea of distributed mechanisms with some detail.

2.3 Functional distribution, redundancy, and cognitive processes

Previous sections indicate that the nervous system is often considered the sole generator of internal activity relevant to behaviour [Farah, 1994][Kien & Altman, 1995], though sometimes the rest of the body may also be relevant [Gallagher, 2005][Clark & Chalmers, 1998]. The idea of behavioural mechanisms that distribute across brain-body-environment might be thought as an additional protection against changes that threaten crucial biological functions, rather than exclusively concentrating on internal mechanisms such as redundant back-ups [Wagner, 2005][Hunter, 2009][Macía & Solé, 2008].

The concept of 'distributed robustness' is gaining awareness in systems biology. In distributed robustness, interactions of multiple parts, each with a different role, can compensate for the effects of perturbations (Figure 2.4) [Wagner, 2005][Félix & Wagner, 2008]. Important concepts for such compensation are 'degeneracy' and 'redundancy', taken from the neural context. The former is the ability of elements that are structurally different to perform the same function [Tononi *et al.*, 1999][Edelman & Gally, 2001]. The latter generally implies an agent-internal-system with redundant parts producing a robust trait at organism level. Félix and Wagner (2008) also have proposed redundancy as one way of favouring the robustness of the system [von Neumann, 1966][Fernandez & Solé, 2004][Wagner, 2005], but the presence of excessive redundancy may increase the effort required.

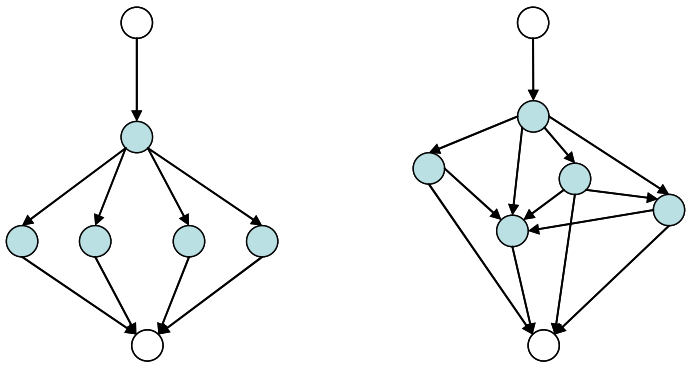


Figure 2.4 – Illustration of distributed robustness and redundancy. Plots show a hypothetical organization in which an upstream signal from upper white circles is processed by a number of intermediate components (dark circles) to a downstream effector (lower white circles). If the relation between processes shows distributed robustness (*right*), it is robust because the flow of information is distributed among several alternative components and flow paths, with no two parts performing the same function. In contrast, if robustness is achieved through redundancy (*left*), several components perform the same function. Adapted from [Félix & Wagner, 2008].

Further philosophical discussions about the structure and the distributive aspects of robustness have appeared. Calcott (2010) reviewed the book of the philosopher Wimsatt (2007) indicating the importance of the distributed nature of robustness, but with certain concerns:

> "[…] the structure of robustness still requires much clarification. How, for example, might the structure of distributed robustness found in biology relate to the structure of robustness for theorems or detection? We can also ask what interactions there are between the various roles that these different kinds of robustness play. For example, what interactions are there between robust phenomena and their detection? This question is relevant to Wimsatt's work on levels of organisation, where the question of robust detection and robust phenomena are not well separated. More work needs to be done to clarify this relationship."

The lack of understanding about distributed robustness is partially attributed to the intrinsic complexity of analyses of the information flow in most agent-inner-control in biological organisms. In other words, the relation between the flow of information that is distributed among several alternative components and the effect of perturbation on such flow is not easy to comprehend in terms of their contribution to the maintenance of global functionalities. For example, the distributed regulation of artificial and natural neural networks illustrates control as neither exclusively centred in any component of the network nor in any particular subset (Figure 2.4-*right*). Neural networks working as control systems are therefore highly robust to removal of synapses or neurons, despite neurons having different roles [Amit, 1989] (see [Beer, 1995a][Clark & Chalmers, 1998][Gallagher, 2005]). The distributed processing is an integrated set of functionalities that are performed by multiple, semiautonomous units [McClelland, 1989].

Another example of functional distribution comes from Krakauer (2005, p. 191): "distributed processing, or connectionism, might be assumed to be a combination of modularity and spatial compartmentalization, but differs in that a single function is emergent from the collective activities of units, and correlated activity is thereby a desired outcome." His observation suggests that one of the benefits of having distributed process in connectionist models is the property of degrading gracefully upon removal of individual nodes.

We investigate other concrete examples in our experimental chapters (from Chapter 5 to Chapter 8). The type of robustness in our experiments lies in the distributed nature of behavioural control mechanisms based on brain-body-environment coupled dynamics rather than functional distributions at 'brain' level. From a cognitive perspective, our examples indicate that coupled internal dynamics with pertinent environmental processes are resources that agents use to reach robustness, where from the agent's perspective the environment acts as an external source of knowledge. This idea is also referred in literature as follows:

> "An agent's physical body, the structure of its environment, and its social context can play as important a role in the generation of its behavior as its brain. Indeed, in a very real sense, cognition can no longer be seen as limited to an agent's head, but can be distributed across a group of agents and artifacts." [Beer, 2003, p. 209] (from a cognitive science context).

> "Robustness is observed whenever there exists a sufficient repertoire of actions to counter perturbations (requisite variety, [Ashby, 1958b]) […]). In many complex adaptive systems (CAS), the actions of agents that make up the system are entirely based on interactions with their local environment, making these two requirements for robust behavior interrelated. When robustness is observed in such CAS, we generally refer to the system as being self-organized, i.e. stable properties spontaneously emerge sans centralized routines for matching actions and circumstances." [Whitacre & Bender, 2009, section 2] (from a complex adaptive systems perspective).

Likewise, neuroscience and cognitive science are beginning to show how behaviour and cognition arise in coupled dynamics [Beer, 2004a, 2004b]. Once we recognize the crucial role of the environment as part of distributed mechanisms in robust systems, we will understand better how to identify and achieve robustness in artificial agents. Discussion around the distribution of behavioural mechanism (in particular in minimal systems) is one of the goals of this thesis. This necessarily involves identifying and characterising the dynamics needed for behaviours that agent-environment interactions produce. These structures are an essentially biological phenomenon, since biological unities can engage only in interactions that affect their structure and maintaining their functionality [Beer, 2004a]. A growing body of research in cognitive science reflects this view [Beer, 1995a, 1997, 2000][Chiel & Beer, 1997][Di Paolo & Iizuka, 2008]. Because we are interested in dynamics associated with the exhibition, persistence, and modification of behaviours in agents, we also focus in this thesis on the idea of distributed robustness and its relation to dynamical cognitive mechanisms (section 2.4).

The next section describes the paradigm we use to contextualize robustness in our own study. Our approach differs from much of the work above in that we employ a holistic perspective (rather than an agent-internal-centred one) rooted on a situated, embodied, and dynamical systems understanding (as we further develop in Chapter 3).

2.4 A distributed account of robustness

In this section, we provide a brief background into the systemic approach that we want to promote in this work. Section 2.4.1 introduces our definition of robustness to use the term consistently and clearly. We discuss some characteristics of distributed behavioural mechanisms in terms of functional dependencies at agent-environment system level. Sections 2.4.1 and 2.4.2 represent part

of the novel contribution of this thesis to robustness research as a focused discussion on distributed behavioural mechanisms.

2.4.1 The promoted understanding of robustness

As we have suggested in previous sections, robustness is a property that allows a system to maintain functionality against internal and external perturbations [Kitano, 2007]. Another definition of robustness from systems biology is "the ability to maintain performance in the face of perturbations and uncertainty" [Stelling *et al.*, 2004]. Because it is important to choose an appropriate definition for addressing any problem of interest, in this thesis we propose a slightly different paraphrasing of previous definitions:

> "Robustness is a capacity that allows an agent (artificial or biological organism) to continue functioning via toleration or adaptation to internal and external perturbations, where this capacity is partially determined by an agent-environment history of interactions."

It is informative then (as the experimental models in this thesis will show) to define robustness as a property of an organism (agent) coupled to an environment in the presence of perturbations. From a biological standpoint, a perturbation is an alteration of a function required by an organism, where perturbations can be induced by internal or external factors. For example, an organism can be perturbed by environmental stimuli (e.g. temperature changes and pressure), motor movements (e.g. a leg stepping into a hole), and small molecules that affect different biological pathways (e.g. drugs and toxins). The conceptual difference that we want to highlight with our definition in comparison to other definitions appears in the consideration of:

(i) those situations in which an agent develops endurance resisting perturbations;

(ii) situations which an agent has not been previously prepared to tolerate situations that were not given during organism evolution.

We propose this definition of robustness because it enables sensible discussion of (a) that to which an agent is robust (e.g. specific perturbations that were presented during evolution), and (b) functionality that is maintained despite perturbations by toleration or changes in the dynamics of the agent-body-environment (i.e. coupled dynamics). Importantly, our definition also suggests a differentiation of pre- and post-perturbation state of an agent-internal-system, which can help us to categorize dynamical changes due to perturbations. The proposed definition also agree with the possibility of perturbing the inner organism (e.g. a part of the nervous system), a trait (e.g. the shape of organism's body through mutilations), or a capability (e.g. the sensory ability).

Our definition is also compatible with a measurable notion of behavioural robustness, which we call *fitness* or the evaluation function. Fitness is hard to define strictly across agent-environment

systems, but we use it as a 'relative quantitative measure' in experimental chapters in this thesis. A change in fitness can indicate less robustness with respect to some task that an agent should accomplish, or robust performance when the fitness remains within certain bounds. Fitness-based measures of robustness are detailed for each experimental scenario in this thesis from Chapter 5 to Chapter 8.

Our definition does not deny the relevance of internal mechanisms *promoting* (instead of ensuring) a high degree of robustness in case of unforeseen environmental or internal changes. In this respect, agents having specialized internal controls monitoring the environment to perform tasks can often have a fundamental advantage in getting information from the state of the environment expediently. Internal control systems in fact remain the most *active* element when understanding behaviours under perturbations in experiments in this thesis.

This thesis promotes the idea, however, that the maintenance of cognitive actions and behaviours under perturbations are deeply permeated by the shape and structure of agent-environment dynamics (Figure 1.1) as opposed to being *solely* determined by the agent's internal structure. This relation between robustness and coupled dynamics is rarely discussed in literature of theoretical systems biology. There is plenty of work however on what kinds of inner structures will tend to be robust. Hence, most of the literature tends to show a one-sided view of the problem, laden on the side of the agent dynamics and not so much on the dynamics of the coupling. For instance, negative feedback is considered in systems biology as the principal mode of control that enables robust response (or robust adaptation) to perturbations as extensively sustained for bacterial chemotaxis [Kitano, 2004a]. The consideration of an internal control system composed of negative and positive feedback is also supposed to be enough to attain a robust dynamic response as observed in a wide range of regulatory networks, including the cell cycle, the circadian clock and chemotaxis [Alon *et al.*, 1999][Borisuk & Tyson, 1998]. Furthermore, integral feedback — a method of feedback control in which control is proportional to the integral of the systems' output [Kitano, 2004a, p. 828] — is thought to be essential to maintain robust adaptation in both *E. coli* and *Bacillus subtilis*, despite differences in network topologies [Rao *et al.*, 2004]. These examples illustrate once more a non-fully appropriated approach for understanding how behavioural robustness emerges in biological systems. If we are to take the study of such lifetime robustness *seriously*, we should carefully scrutinize the traditional notion that agent-internal mechanisms in the inner-environment and body 'ensure' robustness.

A potential *criticism* of our perspective is that usually behavioural robustness is considered in literature as a set of environmental changes (e.g. some living systems are robust to working in the air or under-water). One might think that robustness *cannot* be defined as a property of a system-in-interaction. This thesis still claims that robustness is a property of an agent in isolation (e.g. a robot is made of metal for which is robust to certain environmental conditions that do not affect metals). Nevertheless, robustness is also inherently a property of the coupled agent-environment when some functionality is being maintained by the *full-coupled system*.

2.4.2 Approximating distribution via functional-dependence

In Chapter 1 we suggest that distribution of mechanism is not shorthand for brain-body-environment coupling. If the functionality is distributed (rather than centralized in the brain), the flow of information required to accomplish behaviours is possible between several brain-body-environment processes. Williams and Beer (2009) also noted this issue saying:

> "A common challenge faced by biological organisms and mobile robots alike is the need to adjust motor activity in response to unreliable effectors so as to robustly achieve some behavioural goal. When motor actions fail to produce their desired consequences […] an agent must adaptively reorganize its behavior to meet the changing circumstances and accomplish its objective. Can simple model agents be evolved to exhibit this kind of behavioral robustness and flexibility? If so, what kinds of control strategies will they employ? […]" (from the ER and minimal cognitive contexts).

Most of the experiments reported in this thesis represent examples of this important feature, where evolution devises distributed control strategies in the face of dynamical dependencies to body and environment. For example as we will see in Chapter 8, the pattern of locomotion of a one-legged agent does not always arise from a centralized gait generator (e.g. CPGs in [Beer, 1995a], [Patla, 1991], and [Calvitti & Beer, 2000]). Rather, behavioural control can also emerge as strongly associated to interactions between leg neural patterns mediated by the network of coordination, body feedback as the state of the foot and features of the environment (e.g. the presence or absence of certain level of sensory noise).

The question that arises is *under what conditions do distributed mechanisms emerge?* As Ashby (1960, p. 222) indicated: if for certain reason the flow of information from and to the environment is not possible or difficult, communication within the brain mediated by the environment can be necessary or advantageous. Furthermore, coupled internal control mechanisms also allow an organism to respond quickly and efficiently to individual stimuli and to detect novel situations if present in the environment. Whether these internal mechanisms promote robustness against perturbations, as we will exemplify in Chapter 5, once more, depends on where in the brain-body-environment perturbations take place. We hypothesize that internal control cannot be easily ensured under the effects of perturbations in agent's internal state or in agent's sensory dependencies, for which distributed control across a coupled system may be more convenient. Chapter 6 and Chapter 8 explore this idea with some detail.

It is worth noting with this discussion that we *cannot* always observe the emergence of distributed mechanisms. Therefore, *why should we pay attention to such distribution in relation to behavioural robustness*? The set of possibilities to answer this question includes:

(a) Robustness *always* depends on the agent-environment coupling;

(b) Robustness *sometimes* depends on the agent-environment coupling;

(c) Robustness *often* depends on the agent-environment coupling;

(d) For certain kinds of systems, robustness *strongly* depends on the agent-environment coupling;

(e) Robustness is better understood in the context of agent-environment coupling.

Analysing with some detail the difference between these claims, we can notice that (e) is slightly weaker than other claims because it does not require that agent-environment dynamics are the determinants of robustness in all cases. To understand robustness we need in fact to take the agent-environment perspective. This can be claimed indeed in conjunction with cases (b), (c), or (d). In terms of (a), the dependence of robustness to agent-environment coupling is the strongest option, but we believe it is false (this is the premise of the question). This thesis defends (e) but we also support claim (b).

Claims (c) and (d) are a bit more interesting: (c) because it proposes that we can expect in general some tendency to observe agent-environment dynamics for robust behaviour, and (d) because it prompts us to ask the question, *which kind of system tends to rely more on agent-environment dynamics?* However, (c) and (d) claims are difficult to defend based on results presented here, because one needs to identify how often behavioural robustness depends on agent-environment dynamical engagements, or classify types of systems where robustness strongly depends on coupling.

Therefore, again, the claim that this thesis want to promote is (b): *robustness sometimes depends on the agent-environment coupling*. Experiments reported in this thesis also emphasize that it is not generally appropriate to suppose that the ability to categorize, recognize, and exhibit behaviours in normal situations and under perturbations is intrinsically a matter of agent-internal neural processes and only extrinsically related to bodily inputs and dynamics. Specific environment-engaging loops and patterns of body dynamics make an essential difference in how agents perceive the world and sustain robust behaviours.

Finally, *how can one compare of the distribution of a behavioural control system in relation to another system?* In this thesis, we base such a comparison on perturbation analysis by analysing significant variations in fitness after perturbing elements of our simulated models. For example, in Chapter 7 we study the effects of reducing incoming signals (sensory feedback) during tests in one-legged agents showing walking behaviour. In this scenario, we explore whether further dependence on sensory feedback from an agent's leg is shown in terms of decay in fitness. The particular variables to perturb are selected in this thesis using dynamical systems theory to guide such identification.

Our proposal to study the distribution of behavioural mechanisms is common in computational neuroscience (see [Keinan, 2005]). To determine the distribution criteria, this thesis employs

robust analysis [Wimsatt, 2005][Silverman & Ikegami, 2010][Calcott, 2010]. This is a useful method to account for the distribution of cognitive and behavioural mechanisms in agents by allowing investigation in what specific ways the system-in-coupling can be behaviourally robust. A contribution analysis can be considered a good method to access the distribution for our experimental scenarios because we can objectively account for the effects of induced perturbations in the performance of agents measurable in terms of fitness. Our approach defines operationally the distribution of behavioural mechanisms based on sets of validation tests (i.e. perturbation analyses) to determine the presence of internal-control, body and environmental factors required for behaviours. In this way, we use a definition of distribution that relies on operations in order to avoid trouble associated with attempting to define this concept in terms of some intrinsic essence of our models. This approach is in contrast to 'operationalization' (a more intuitive approach) that uses theoretical definitions (see [Vandervert, 1988]).

Another possible alternative to compare systems in terms of distribution is by studying causal contributions from computational neuroscience is Granger Causality (G-causality) as described in [Seth, 2005] and [Seth & Edelman, 2007]. These works discuss the joint product of network structure and the dynamical processes operating on that structure, which may be modulated by environment and context. Seth and Edelman show how the same network structure can generate different causal networks depending on context. G-causality has been applied to simulated neural systems to probe the relationship between neuroanatomy, network dynamics, and behaviour. Despite its relevance to neuroscience, this thesis does not apply G-Causality as measure of distribution of mechanisms because our interest is in a more traditional approach derived from perturbation analysis, comparable to current studies in systemic robustness.

2.5 Remarks

This section highlights some of the main points given in this chapter in order to help the reader to better understand discussion in the following chapters.

- *None* of reviewed works claims that the environment plays absolutely no role in deciding whether a system is robust or not, and while this chapter promotes the relevance of interaction, internal dynamics remain essential elements. The real contribution of the thesis is investigating coupled dynamics for behavioural robustness in simple models from a computational way, which had not previously been reported (see [Hubert *et al.*, 2009] and [Silverman & Ikegami, 2010]).
- The growing consensus about the importance of brain-body-environment couplings is still *a minority view* in several disciplines. These include cognitive psychology, neuroscience, a good part of AI and robotics, and indeed several areas of biology. It is to be expected that even for those who agree on the view promoted in this thesis (i.e. the distribution of mechanisms promoting behavioural robustness), the full implications of it have not fully

been drawn, and this thesis attempts to address the proposed issues as indicated in Chapter 1. This motivates the thesis for the particular topic of behavioural robustness.

- Robustness studies *have not typically been approached* from the point of view of coupled dynamics. Robustness is usually attributed to a control system in general, but it may well turn out to be a property of a particular agent-internal-control in its environmental coupling. Hence, the need to untangle the contributions to robustness from different factors (e.g. internal, interactive, and environmental) that this thesis promotes. Furthermore, it is also the case that the relation between distributed mechanisms and behavioural robustness *has not been investigated* by means of minimal behavioural models (i.e. using the ER methodology).

2.6 Final comments

In this chapter, we propose that to comprehend robustness in a variety of fields, one must adopt a holistic view of system dynamics. Understanding the structure and dynamical properties of isolated components in an agent-internal-system is important if we want to know functional aspects of specific components (e.g. neural assemblies producing activities 'inside the brain'). However, to recognize properties of a highly coupled system one must view the system as a whole.

As illustrated by Figure 2.5, identifying all structural and dynamical properties of components in an inner-system (i.e. internal-agent environment) without seeing the overall picture is like describing all the parts of a house without account for the relation between rooms. While such a description provides clarity of the individual components, by itself it may not be sufficient to encompass the full dynamics of house functionality. We must also analyse the functional relations between rooms in a house, and the network of wires that link the rooms (Figure 2.5). Only in this way can we fully understand how the organization of components sustains a house as a system.

This thesis uses a systemic perspective to investigate robust behaviour, looking for answers to questions such as: *How are the dynamics of a system organized to sustain behaviours despite perturbations? How do internal control systems in a particular model face perturbations that were presented (or not) during system evolution?*

This concludes our survey in this chapter of holistic robustness research, motivating the brain-body-environment, and in-silico dynamical systems approach. The next chapter concentrates on related work in artificial systems as opposed to biological. The ER research described in Chapter 4 introduces the ideas behind creating simulated models to explore robustness in embodied, situated, and dynamical agents (Chapter 3).

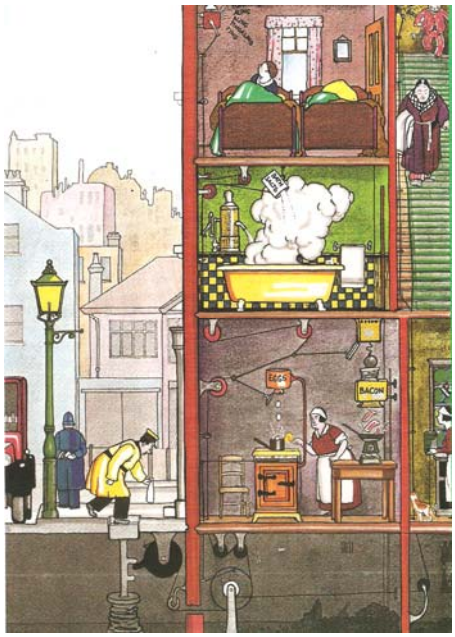


Figure 2.5 – A metaphor for cell signalling with the milkman as an external factor in the control of internal events. The metaphor illustrates the relations between components of the house-environment system and the processes that occur inside the house due to external factors (e.g. the presence of the milkman triggering the preparation of food in the kitchen). A deeper look into this figure will reveal that concentrating on some of the components (e.g. the kitchen) will not reveal what produced the preparation of food, and the related processes running simultaneously in other rooms of the house (e.g. the preparation of the bathroom). This simple metaphor shows us the relevance of the holistic understanding of processes in a system rather than concentrating on properties of isolated components. Figure from [Varmus & Weinberg, 1993, Chapter 6].

Chapter 3

An agent-environment approach: concepts from Adaptive Systems

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"All doing is knowing and all knowing is doing."

Maturana and Varela, 1992

In Chapter 2 we introduced a growing research trend, mainly in the fields of cognitive science, neuroscience, and bio-inspired neuro-robotics to refocus on coupled behaviour between brain, body, and environment. Current systems biology recognizes the relevance of distribution of robustness across systemic components. However, the role of distribution of mechanisms enabling behaviours and robustness has rarely been discussed in the literature of these fields, which so far has investigated only localized mechanisms. This chapter presents a brief overview of conceptual frameworks used in this thesis to study systemic robustness from an agent-environment coupled perspective. We introduce initially the main conceptual framework used in this thesis — situated, embodied, and dynamical systems. Part of this chapter also provides an illustrative account of dynamical systems theory useful for understanding the following experimental chapters. The chapter continues with explanations of some computational studies from the cognitive context. This chapter concludes with examples from ER on the distribution of behavioural and cognitive mechanisms (the full ER methodology is described in Chapter 4).

3.1 From behaviours to coupled engagements

A paper by Brooks (1986) started Behaviour-Based Robotics (BBR), which focuses on the construction of robots, architectures for controlling mobile robots, and robots that successfully

operate in the noisy, complicated physical world [Brooks, 1989, 1990, 1991a, 1991b, 1991c, 1992] (see also [Brooks & Flynn, 1989]). Over the years, the idea has been the nucleus of several controversial discussions within classical AI [Kirsh, 1991][Brooks, 1997]. BBR proposes implicit environmentally linked control, rather than representing the world as propositions logically manipulated by 'a solving-task algorithm'.

In AI research rooted on logic and problem solving, GOFAI (Good Old-Fashioned Artificial Intelligence) [Haugeland, 1985] represents the oldest original approach to achieving intelligence in artificial systems. The approach assumes that many aspects of intelligence can be achieved by the manipulation of symbols. The position of symbolic AI promoters was that 'representationalism' is the way that minds work in nature. One of the main characteristics of GOFAI is 'functional decomposition' — the process of resolving a functional relationship into its constituent parts in such a way that the original function can be reconstructed from those parts. Brooks criticised the use of such decomposition to design robotics control systems because it is not clear how such division should be made. Instead, Brooks advocated behavioural decomposition.

Behavioural decomposition dictates that desired behaviours be broken into a series of local actions or simple behaviours [Brooks, 1991a]. Each module implementing an action requires an 'initiator' to enact, e.g. the presence of a specific situation in the environment to respond [Brooks, 1989]. The idea behind this decomposition is to create isolated, low-level behaviours that can be first tested on a physical robot. That is, the robot is placed in its operating environment to ensure that all the actions work before they are coordinated by the high-level, robotic control system. This composition of actions or simple behaviours can create more-complex actions when they are properly coordinated to accomplish a complex task (see [Fernandez-Leon, 2006] for an example with mobile robots). A key feature of behavioural division is that the representation of the environment plays little part in the low-level behavioural design process, but an important one in the definition of behaviours. Rather than representing the environment as an 'internal model' through a set of propositions within the robot's controller (e.g. the positions of objects in the environment and paths to follow), the environment can act as its own model [Brooks, 1991a, p. 15].

The lesson that arises from Brooks' work is that robots have the potential to respond directly to an event in their environments, rather than reacting to events via an *internal* environmental model. A complex behaviour (i.e. a behaviour composed of different simple, low-level behaviours), may consist of the proper coordination of modules contributing to accomplish a high-level task (see [Acosta *et al.*, 2010] for an example of behavioural coordination). For instance, the task of safe navigation in unknown environments, where a robot should move from one starting position to another one (goal), can be obtained by the combination of reactive goal-approaching and object-avoiding behaviours implemented as separated behavioural modules [Fernandez-Leon *et al.*, 2004].

Considering Ashby's (1960) and Walter's (1951, 1953) works from the cybernetics field [Ashby, 1956], Brooks raised the idea of *engagements* grounded on 'situated' (section 3.2.1) and

'embodied' (section 3.2.2) properties of robots. Following those ideas, but using the language of dynamical systems theory, Beer (1995a) proposes a general conceptual framework for the synthesis and analysis of autonomous agents and their environments. The essence of his proposal is that coupled dynamics in brain, body, and environment are in general jointly responsible for agent behaviour. In this respect, Pfeifer *et al.* (2005) indicate:

> "Strictly speaking, behavior is always emergent, as it cannot be reduced to internal mechanism only; it is always the result of a system-environment interaction. In this sense, emergence is not all-or-nothing phenomenon, but a matter of degree: the further removed from the actual behavior the designer commitments are made, the more we call the resulting behavior emergent. Systems designed for emergence tend to be more adaptive and robust."

The following sections briefly describe associated concepts, as well as other definitions used in this thesis, with special emphasis on their relations with behavioural robustness.

3.2 A framework for cognitive research

Beer (1995a) introduces a framework for studying agent cognition through the so-called *situated*, *embodied*, and *dynamical systems* approach. He bases most of this framework on the understanding of Ashby's (1960) together with Maturana and Varela's (1987) works. This methodology largely promotes the use of dynamical systems theory [Strogatz, 1994] to explore *behavioural* system dynamics. It focuses on the adaptive fit between an agent and its environment as a satisfaction of a given constraint on the dynamical trajectories of the coupled system. In this sense, it follows Ashby, who was one of the first researchers to attempt to understand the mechanisms underlying adaptive behaviour using a dynamical systems perspective (see [Ashby, 1960, p. 130-138]).

Despite the analytical overtones, Beer's attempt to comprehend adaptive behaviour mainly follows a case-study viewpoint, since "there is nothing like studying birds or trying to build an airplane to cut to the heart of the debate about what can and cannot fly" [Beer, 1998, p. 630]. By using simple studies of precise mathematical simulations, we can therefore ask more about the nature of a research problem [Beer, 2003, p. 239]. This work lends back to the concepts of situatedness and embodiment discussed in the next sections.

3.2.1 Situatedness

In robotics terms, 'situatedness' (or being situated in the environment) means that agents (artificial organisms or robots) use spatio-temporal situations in their surroundings directly influence the future behaviour of agents [Brooks, 1991d, p. 1227]. In the computational paradigm, robots can be seen as *agents* because they have access to the effects of their environmental actions. This implies

that agent behaviour while processing environmental signals depends on *where* the agent is placed, *when* the agent senses the environment, and *what* state the environment is in during sensing.

One of the requirements of situatedness is that agents themselves must *control* the whole interaction within the agent's immediate environment (the set of signals in the environment that an agent can sense). This control indicates an agent-centred viewpoint, as opposed to an external perspective on the exhibition of behaviours. The agent's experience of interactions with the environment forms part of the control that produces the agent's actions in the environment [Pfeifer, 1996, p. 5].

Agents are *autonomous*, in that there is no intervention of robot's designer in the agent's behavioural processes. In the biological realm, the agent's immediate environment has 'meaning' from its own perspective, and can be viewed as perceptual cues (see [Beer, 2008, p. 3][von Uexküll, 1957][Ziemke & Sharkey, 2001]). Such meaning is an important part of agent's situatedness because environmental cues enable the initiation, modification, or termination of behaviours [Macinnes & Di Paolo, 2006][Macinnes, 2007].

Situatedness implies two main sources of implicit knowledge available for an agent: the agent's *internal state* and *the state of the environment*. An example from the biological realm is supported by [Bleeker *et al.*, 2006] in that differences in memory dynamics (internal state) between two closely related parasitoid wasp species (Cotesia glomerata, and C. rubecula Hymenoptera: Braconidae) can produce different reliable behaviours in response to perturbations as sensory noise and changing environments (state of the environment). These species, when searching for caterpillar hosts, use host plant odours that are released upon feeding by the caterpillars. This example shows us that the situatedness of parasitoid wasp species and behavioural robustness (e.g. searching for caterpillar hosts in changing environments) relate.

We can also further study the relation between cognitive capacities of agents as a process of interaction with the environment despite perturbations and the presence of certain environmental stimulus that agents use to accomplish behaviours. The cognitive paradigm helps us to better understand the behavioural competences of agents in our implemented agents (from Chapter 5 to Chapter 8). In these experiments, the cognitive mechanisms of agents is associated with their activities in the environment mainly though that which agents can sense. Agents are situated, in that they depend on environmental cues for behaving, and not only on internal (autonomous) components. In our models, situated agents have the capacity of moving in their surroundings, and therefore all agents sensing is co-determined by agent-environment activity. In the simplification, this idea may teach us some of the core fundamental issues in cognitive science and adaptive behaviours research. Beer (2003) develops a series of simple idealized, embodied, and embedded model agents, each of which is capable of minimally cognitive behaviours. He argues that by proceeding in this abstract way, experiments are not constrained by the biological understanding of a research problem.

3.2.2 Embodiment

Embodiment refers to the physical existence of a robot or organism in the environment having a co-related, but essentially different, dynamics from the environment (see [Ziemke, 2001, 2003] for a classification of embodiment). Brooks (1991d, p. 1227) has argued for the importance of embodiment by encouraging robot designers to test and correct robot behaviour in physical scenarios rather than in simulations. According to him, this process of correction must take place on a physical robot as well as in a simulated one, because the difficulty of transferring behaviours from simulation to reality (see [Jakobi *et al.*, 1995] for a partial solution of this inconvenience). Brooks also believes that working with physical robots reveals problems that are complicate to model in simulated robots. Going further, Pfeifer (1996, p. 5) has suggested that an agent existing only in simulation would not be complete.

From a cognitive perspective, embodiment associates to situatedness in that the body is the way that a robot or an organism interacts with the environment [Pfeifer, 1996]. A body with particular perceptual and motor capabilities enables certain kinds of experiences that come from having such a body. Preliminary work of Macinnes (2001) discusses the concept of 'embodied cognition', concentrating on hardware aspects of ER from a simulated-physical world approach. Embodied cognition proposes that the nature of the human mind is largely determined by the form of the human body, which is promoted by some philosophers, cognitive scientists, and artificial intelligence researchers [Wilson, 2002]. A similar concept from the theoretical biology research field is 'enactivism' [Varela *et al.*, 1991][Maturana & Varela, 1992].

In terms of behavioural robustness, the actions of an agent can produce damage to the body due to environmental perturbation or internal malfunction. Only the bodies of living organisms and robots with special control systems can be repaired by specific mechanisms. For example, glia cells (non-neuronal cells) provide support and protection for the brain's neurons [Azevedo *et al.*, 2009]. Glia cells have a role in the regulation of repair of neurons after injury. Detection and action following injury or severance in the human brain, recruits different components in order to rebuild the original body and functionality.

The relation of the body and behaviours in agents mainly obeys to physical considerations such as degrees of freedom of actuators, layout, and characteristics of sensors [Beer, 2008, p. 8]. The relation between embodiment and robustness as a property of behaviours however is not straightforward. The issue is exemplified by the capacity to tolerate or to adapt to perturbations in terms of controlling movements. Collette *et al.* (2007, 2008) have discussed the human capability of keeping dynamical balance during complex task movements. They have investigated the difficulty to adapt to these capabilities using humanoid robot movements in terms of control posture. In presence of external perturbations, object grasping produced by unilateral contacts of an artificial hand can be less effective than bilateral grasp with friction. The latter allows for arbitrarily pulling, pushing, or twisting on a handhold better than the former method. Body shape (in this case, a hand) plays an important role in hand grasping, where some properties of the hand

(e.g. bilateral grasp) permit better grasping despite external perturbations (perturbations on pulling, pushing, or twisting on a handhold).

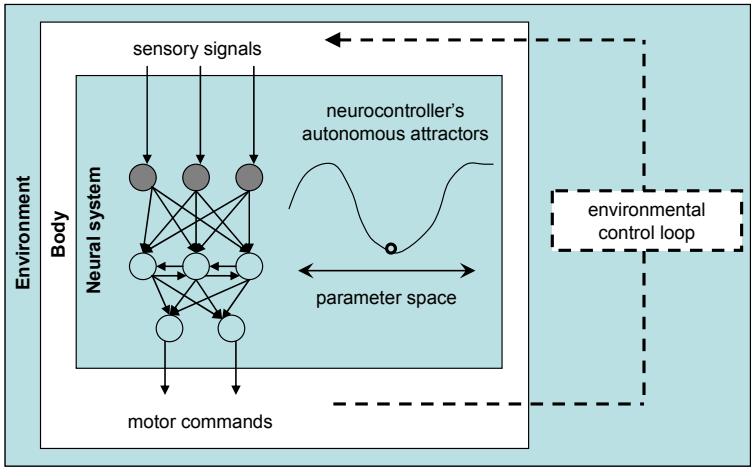

Figure 3.1 – Sensorimotor loop in an embedded neural network context. This is a general representation of an embedded neural network in the body of an agent that is also embedded in the environment. Circles represent neuron-like units that create network output signals for body actuators. Grey circles stand for sensors or input units providing incoming signals to the neural network. Figure adapted from [Wischmann, 2007].

Fine *et al.* (2008) discuss the dynamical importance of embodiment. They investigate the dynamical processes used by an evolved, embodied, and simulated agent that adapts to large disruptive changes in its sensor morphology whilst maintaining goal approaching (phototaxis) behaviour. Fine *et al.* (2008) argue that adaptive processes of the agent are related to its body morphology based on the relationship between different timescales within the agent and the environment (e.g. neuron and behavioural timescales). Interestingly, the dynamics of the agent controller and different behaviours in Fine *et al.*'s experiments depend on the agent's current sensor layout and the internal-agent-transient dynamics of coupled dynamical states. In other words, there is an important relation between embodiment and dynamical relations, and also with variables of the agent's environment and agent's 'brain'.

The models that we present in our experimental chapters simulate only some aspects of embodiment, though all models are situated. Our agents produce motion by processing the information received from sensors and applying control actions to actuators (Figure 3.1). In particular, Chapter 7 researches embodied agents that can change the way that they receive sensory information based on environmental experience. This change is made possible through self-induced modifications of agent sensors following Macinnes's and Di Paolo's (2006) ideas of the evolution of 'sensory offsets' (further explained in Chapter 7).

3.2.3 Dynamical systems

Beer and other researchers have opened a broader set of possibilities through dynamical systems theory to understand how situated and embodied agents show, maintain, and modify their behaviours. Beer (1997, p. 260) proposes that:

> "A situated agent receives a continuous stream of sensations from its environment and produces a continuous stream of actions which continuously depend both on its sensations as well as its own changing internal state. This suggests that the proper way to model an agent is as a dynamical system."

The dynamical understanding of behaviours is of particular importance in robustness research. Dynamical systems theory helps us to comprehend behavioural robustness in the presence of perturbations that modify or 'break' normal functioning. From a biological systems context, Kitano (2004a, p. 835) also suggests the importance of certain dynamics in mechanisms that evolved in an agent's internal environment to deal with certain perturbations:

> "Enhancement of robustness against perturbations can be made through the combination of these [system controls, modularity, alternative mechanisms and decoupling] mechanisms, but system control is the prime mechanism for coping with environmental perturbations that require proper dynamics."

Further works from literature discuss the importance of dynamical interpretations in neuroscience and coupled non-linear systems. Using the neuroscientific approach, Rabinovich *et al.* (2008) have focused on agent-internal-dynamics working in transients with robust and sensitive properties to external and internal factors (see also [Rabinovich *et al.*, 2006][Afraimovich *et al.*, 2004][Mazor & Laurent, 2005]). From a discrete dynamical systems approach, Demongeot *et al.* (2008) have researched a method for understanding (agent-internal) systems by focusing on basins of attraction when structural changes are induced on regulatory networks, influencing the properties of these basins of attraction.

In the next section, we describe some relevant concepts of dynamical system theory useful to understand the dynamical discussion on robust and adaptive behaviour given in the rest of this thesis. Because we use experimental models working with continuous-time networks (section 4.3.1), the explanations of the next section refer to concepts from differential equations and non-linear system descriptions. In other words, we centre on non-linear dynamics to represent the dynamical behaviour of neural systems. For a more rigorous description of dynamical systems theory refer to [Strogatz, 1994].

3.2.3.1 Basic concepts of non-linear dynamical systems

Because of the complexity of non-linear systems' analyses, we mainly follow a similar methodology to Beer (in press) in analysing minimal models using dynamical systems tools. These analyses are mainly suited for studying embodied, situated, and dynamical agents, and chiefly focuses on variables rather than in parameters of the system. That is, the changes of a variable overtime will depend on a subset of all state variables in the system given a set of parameters (see [Izquierdo, 2008] for dynamical examples with this approach).

Some of the primary concepts in dynamical systems theory are as follows. A *dynamical system* is represented by a set of *state variables* and *dynamical laws* that govern how the values of variables change over time. A dynamical system can be linear (i.e. when state variables changes linearly) or non-linear (i.e. when state variables have non-linearity). This classification depends on how the dynamical laws act on the system's state variables. State variables represent by their values the position over time of a system in a dynamical space. The *state space* of the system is the set of possible values that state variables can reach following the dynamical law or vector field in such space.

A *dynamical trajectory* of the system is the sequence of states generated by the action of the dynamical law starting from some initial state. The *dynamical flow* is the set of all dynamical trajectories through every point in the state space, where a picture showing all of the qualitatively different dynamical trajectories of the system is called a *phase-portrait* [Strogatz, 1994]. A phase portrait is a geometric representation of the trajectories of a dynamical system in the phase plane for fixed values of parameters. Each set of initial conditions is represented by a different curve or point. *Attractor states* are sets of points that remain invariant under the dynamical law in the state space. *Stable attractors* have the property that all trajectories passing through all nearby states converge to it, where the set of initial states that converge to a given attractor is termed its *basin of attraction*.

A *limit set* is the state that a dynamical system reaches after an infinite amount of time has passed. Limit sets are important because they can be used to understand the long-term behaviour of a dynamical system. Examples of limit sets include stable *fixed points* (or point attractors), *limit cycles* (or stable orbits), saddle points, and unstable fixed point repellors. A *saddle point* is a point in the domain of a function that is a stationary point but not a local extremun. Equivalently, a saddle point is a point in state space having stable and unstable manifolds with a dimension that is not zero. Limit cycles and similar dynamics present a particularity, among other reasons, because they represent dynamical pattern of a system that oscillate even in the absence of external input (see Chapter 7 for some related discussions).

A point in parameter space stands for a specific combination of all parameter values and thus is related to a fixed set of basins of attraction and attractors in the corresponding state space of the dynamical system or phase portrait. A *bifurcation* occurs when a small smooth change made to the parameter values of a system (the bifurcation parameters) causes a sudden qualitative or topological change in system behaviour [Blanchard *et al.*, 2006]. For experimental analyses in this

thesis, parameter space is the space where the axes refer to the parameters of an artificial neural network. In the case of a *continuous-time recurrent neural network* (CTRNN) (further explained in section 4.3.1), these will be synaptic weights, time-parameters, biases, etc. A search in this space is possible for some optimal combination criteria of parameters (e.g. using artificial evolution as explained in section 4.2) for points (or regions) in this parameter space that have high fitness (see Figure 2.2).

When we have a specific evolved neural network working as an internal control system embedded in an agent body with specific network parameters fixed, we refer to the *phase space*. We then observe the changing values of activations of each neuron, input values, output values, possibly position and orientation values of the agent in its environment. In this space, all possible states of a system (or allowed combination of values of the system's variables) are represented with each probable state of the system corresponding to one unique point in the phase space. It is worth to note that bifurcations then happen in phase space, rather than in parameter space. Phase state from mathematics field is a similar concept than phase space in control engineering, where axes are the parameters (see [Strogatz, 1994]).

In terms of small perturbations, the dynamical systems analysed in our experimental chapters are structurally stable. This indicates that small variations in the parameter values will produce little changes in the dynamical flow, where limit sets and basins of attraction may slightly deform and move, but the new flow will be qualitatively similar to the one before the perturbation [Demongeot *et al.*, 2008]. This observation suggests that a system can remain relatively unaltered despite small variations in its components and relations regardless of the effects of perturbations on the structure of a system (section 1.1.1). Consequently, the looseness involved in determining the size of a perturbation is because it is a function of maintenance of the systemic structure. Section 2.2 extends this observation concentrating on the concept of 'structural stability' in that small variations of components (and their relations) can produce non-significant changes in the dynamics of a system [Jen, 2003]. The next section introduces other basic concepts of dynamical systems theory following explanations in [Strogatz, 1994], [Rabinovich *et al.*, 2008], [Izquierdo, 2008], and [Kitano, 2004a, 2007], among other works.

3.2.3.2 Emphasis on internal transient dynamics during coupling

One of the most interesting phenomena in a neural system is the presence of non-stationary behaviour. Attractor dynamics usually implies long-time evolution from initial conditions, but the important behavioural activities of neuronal systems cannot be understood by analysing attractor dynamics alone; rather we need to see these dynamics when coupled with the environment.

Transients are the parts of the trajectories that do not lie on attractors, moving toward, between, or around point or cyclic attractors in the full state space (see [Strogatz, 1994] for more precise definitions). This perspective on internally transient dynamics related to agent-environment interactions helps us to understand what is going on 'inside the brain' rooted on agent's body and its interaction with the environment. Transient dynamics have also been investigated previously in

cognitive processes. For example, Rabinovich *et al.* (2008) have argued from a computational viewpoint of how perception and cognition can be modelled as dynamic patterns of transient activity within neural networks.

As we discussed in this chapter and in Chapter 2, the majority of studies in robustness during agent lifetime focus on agent-internal properties rather than on dynamical aspects of the whole agent-environment system. In fact, internal systemic dynamics that are also robust to perturbations are conventionally thought to be both necessary and sufficient to account for behavioural robustness (see [Rabinovich *et al.*, 2006][Afraimovich *et al.*, 2004][Kitano, 2007]). Recent theoretical and experimental works in neuroscience have attempted to resolve this dissonance by suggesting that robust behaviour of key biological and cognitive processes can be grounded on (internal) transient dynamics [Rabinovich *et al.*, 2006].

Understanding how internal dynamics shapes behaviour is a major issue in cognitive and robust systems research [Rabinovich *et al.*, 2006, 2008]. This interest rises because it is usually though that complex and heterogeneous networks interacting nonlinearly generate the internal transient dynamics that operate within living organisms. The activity of agent-internal components in Rabinovich *et al.*'s scenarios changes over time as a function of other components. In an environmentally coupled agent context, the dynamics of agents is constantly changing due to variations of stimuli that depend on an agent's situatedness. In this, Rabinovich *et al.* (2008) propose a computational view of how perception and cognition can be modelled as dynamic patterns of transient activity within neural networks:

> "Transient dynamics have two main features. First, although they cannot be described by classical attractor dynamics, they are resistant to noise, and reliable even in the face of small variations in initial conditions; the succession of states visited by the system (its trajectory, or transient) is thus stable. Second, the transients are input-specific, and thus contain information about what caused them in the first place. Notably, systems with few degrees of freedom do not, as a rule, express transient dynamics with such properties. Therefore, they are not good models for developing the kind of intuition required here. Nevertheless, stable transient dynamics can possibly be understood from within the existing framework of nonlinear dynamical systems."

As we previously described in section 2.2, the state of an agent-internal-system can be shown as a point in the state space where perturbations can move such point to a different position in the state space. The state of the internal system might return to its original state (or attractor) by adapting to perturbations, often using a negative feedback loop [Kitano, 2006] (or by tolerating these perturbations [Di Paolo, 2005]) and remaining in a qualitatively different region, i.e. a perturbation might 'push' the internal transient dynamics of the inner-system far from the basin.

From a neural context, this explanation suggests that the neural phenomena in biological organisms often occur on very short time scales where classical attractor states (e.g. fixed points or

limit cycles) cannot be realistically reached and the agent-internal-system mostly works in these transient dynamics when viewed at the appropriate perspective. Indeed, behavioural and neurophysiological experiments have revealed the existence and functional relevance of dynamics that, while deterministic, cannot be described as reaching classical attractor states [Uchida & Mainen, 2003][Jones *et al.*, 2007]. Several works in literature support similar observations of internal-transient dynamics working in combination with stable space states (e.g. [Fine *et al.*, 2007][Izquierdo & Bührmann, 2008][Iizuka & Di Paolo, 2007a][Froese & Di Paolo, 2008][Gigliotta & Nolfi, 2008]). Another alternative less explored is 'chaotic itinerancy' [Tsuda, 2001][Ikegami & Tani, 2001][Hashimoto & Ikegami, 2001]. This thesis is not concerned with this last exploratory line of research.

The agents analysed in Chapter 6 usually exhibit transient dynamics at neurocontroller level around one global attractor or between several of them when coupled with the environment. We also describe situations where internal transient dynamics emerge due to agent embodiment (Chapter 6), intrinsic dynamics (Chapter 7), or the agent-environment system's history of interactions (Chapter 8). The next section describes how the situated, embodied, and dynamical framework introduced in this chapter explains cognitive mechanisms that distribute in brain-body-environment.

3.3 Distributed cognition approach

Simon (1981) have shown that "the trajectory of an ant in a beach tells us more about the beach than about the ant", indicating that by observing ants movements we may learn as much about the environment for thinking as we learn of the thinking itself. This observation suggests that mechanisms exhibiting behaviours can oftentimes usefully be approached from a distributed point of view; e.g. by observing how organisms use their environments for particular behaviours.

Distributed cognition is a hybrid approach to studying most aspects of cognition, from a cognitive to social and organisational perspective. It is a psychological theory developed by Hutchins (1995). One major thread is the idea of distributed (cognitive) processes among the members of a social group, and also of processes which are distributed through time in such a way that the products of earlier events can transform the nature of related events. Distributed cognition looks for a broader class of cognitive events and does not expect all events to be encompassed by the skin or skull of an individual, or inside a smart control system in robots [Gallagher, 2005]. This approach pertains to our work, since embodied agents exhibiting behaviours can be interpreted as cognitively distributed among internal-control, body, and environmental dynamics. Some of the foundations that support distributed cognition are given below.

3.3.1 The role of the material environment

Previous sections introduce the idea that cognitive activity can be situated in the physical world in such a way that the external environment is part of the cognitive mechanism of agents acting in

the environment. Clark and Chalmers (1998) have discussed this issue in relation to the potential of the material environment to support memory. However, the environment can be more than a memory. According to Norman (1993), 'cognitive artefacts' in our close environment (those that help the emergence of cognitive actions) are the things that make us smart. The use of artefacts amplifies, in some sense, our cognition capabilities. According to Hutchins (2000), cognitive artefacts (environmental objects) are involved in a process of organizing functional skills into cognitive functional systems. For example, Clark and Chalmers (1998, p. 9) exemplified this situation as follows:

> "Now consider Otto. Otto suffers from Alzheimer's disease, and like many Alzheimer's patients, he relies on information in the environment to help structure his life. Otto carries a notebook around with him everywhere he goes. When he learns new information, he writes it down. When he needs some old information, he looks it up. For Otto, his notebook plays the role usually played by a biological memory. Today, Otto hears about the exhibition at the Museum of Modern Art, and decides to go see it. He consults the notebook, which says that the museum is on 53rd Street, so he walks to 53rd Street and goes into the museum."

This example is commonly viewed as Otto's attempt to extend his memory capabilities despite the brain disease. Cole and Griffin (1980) have argued that this is not the case: it is not memory-amplification, but just an example of the uses of different *functional* skills to do the memory task. Internal and external (material or environmental) structures can initiate, promote, or help to sustain cognitive processes. In this respect, the operation of a cognitive system as a whole involves coordination between brain, body, and environmental processes as we have previously discussed.

Processes enabling cognitive behaviour may be distributed through different dynamical systems and in time in such a way that the results of earlier events can transform the nature of later events. Consider for example the 'trails on grass' system [Goldstone & Roberts, 2006][Helbing *et al.*, 1997]. This system consists of paths made naturally by pedestrians on areas that are covered with grass. Trails are made by the action of walking which makes it difficult for grass to grow in zones which is frequently trodden upon. The lack of grass makes walking along the trail easier and people tend to use the trail rather than cutting across the grass, even if this implies a small deviation from the optimal route to their destinations. The process is self-reinforcing and in the bigger picture, it is a historical process. As Di Paolo (2001, p. 655) proposes:

> "Once a pattern of trails is formed the history of the process has become partially embodied in it and walkers are constrained by its shape to walk along the trails. Thus the pattern modulates the dynamics of the process but, at the same time, is constantly being constituted by the process as trails can only be maintained if enough people use them."

The proposed example, despite being taken from a social interaction context, shows us that the distribution of the cognitive mechanism that enables the walking behaviour of agents (humans) to destinations, is based on the *use of information from the environment* (trails on the grass). It is not the cognitive performance and expertise of any one single person that is important for the maintenance of the trail paths system, rather the distributed cognition over all people using the field, including, but not limited, to the grass field as a whole [Di Paolo, 2001]. This sort of cognitive distribution is extremely important in coupled systems.

The trail path situation exemplifies the dynamics of the system (humans and field) in the end based on agents with the habit to follow defined paths. Nevertheless, if some new person is included, or some perturbation to the grass-field appears, agents will tend to reinforce or create new environmental links in his first attempt to go to his destination, for example by choosing one milestone in its surroundings to guide its walk. It is clear that the mode of environmental influence, whether weak or strong, changes over time and that this is a property of the agent's own internal dynamics and its history of interaction with the environment. In this concern, Di Paolo and Iizuka (2008) indicate that during periods of high susceptibility to external variations, an agent is highly responsive to environmental changes resulting in less commitment to a particular task (e.g. when agents are looking for a given target as a trail on the grass). By contrast, during periods of weak susceptibility (e.g. when agents walk following a trail toward a specific target), walking is consequence of low responsiveness to environmental changes. What this observation tells us is that in all cases walking behaviour in a human-trail path system is the outcome of a tightly coupled sensorimotor loop (Figure 3.1). The idea of cognition as distributed in brain, body, and environment system is also supported by further examples in [Ziemke *et al.*, 2004][Chiel & Beer, 1997][Beer, 1995a][Gallagher, 2005], among other works, where the distribution of the cognitive mechanism in time also emphasizes the importance of the environment for cognition.

Our belief is that to contextualize the distribution of organism's cognition, one must understand the dependencies of control (inner) functionality that emerges from agent, body, and environmental dynamics. These inter-dependencies are required by particular agent behaviours given certain environmental *restrictions*, and will provide novel opportunities to maintain functionality in the presence of perturbations (see [Chiel & Beer 1997][Scheier *et al.*, 1998]). In fact, constraints on an agent are generally derived by embedding brain-like systems in a body [Scheier *et al.*, 1998]. Ashby (1956, p. 130) has discussed this point saying: "[…] when a constraint exists advantage can usually be taken of it." Advantage, in this context, refers to the use of some features of the body and environment in order to exhibit coherent behaviours in relation to the environment's current state. The processes that an agent produces may also exploit body and environment to accomplish particular tasks [Ashby, 1960, p. 61].

Cues from the environment are an integral part of agent behaviours as von Uexküll (1926) suggested (cited in [Ashby, 1940]). Macinnes and Di Paolo have investigated this last point using ER [Macinnes, 2007][Macinnes & Di Paolo, 2006]. The distribution of behavioural and cognitive mechanisms that biological organisms exploit also suggests that the distribution of cognition is a biologically plausible basis on which to investigate behaviours. Recent works from computational

biology [Freilich *et al.*, 2010] and systems biology [Kitano, 2002, 2007][Wagner, 2005, 2007] suggest robustness is affected by the distribution of inner-system functionality among components. Calcott (2010), based on the book of Wimsatt (2007), notes this tendency toward functional distribution in theoretical biology field. Overall, the understanding of the properties underlying robust systems is changing from an agent-centric view to a set of distributed systemic properties that depend on conditions in the organism and environment as a whole. Importantly, to model relatively complex worlds as in our non-linear experimental models, we use idealized representations of the feature of the worlds that we want to study (e.g. different ways to induce the emergence of distributed behavioural mechanisms). Given these idealizations, we need to be sure that results derived from these models tell us about the world, rather than simply reflecting the particular idealizations of the models. The next section continues with explanations of distributed cognitive mechanisms from an ER perspective.

3.3.2 Distributed cognition in Evolutionary Robotics research

Despite the emphasis on coupled agent-environment interactions in general, ER (see Chapter 4) has been paid relatively little attention to work on distributed cognition [Ziemke *et al.*, 2004]. Instead, ER has derived much of its inspiration from Brooksian behaviour-based AI as we discussed in section 3.1, following principally an anti-representationalism, computational, and minimalist bottom-up approach [Beer, 1990, 1995a, 2003].

Cliff *et al.*, (1993) have suggested that ER follows the behaviour decomposition method of behaviour-based robotics. This means that the active adaptation or modification of environments has also been studied relatively little in robotic experiments [Chandrasekharan & Stewart, 2004]. ER research in behavioural robustness can learn a number of lessons from cognitive distribution in embodied, situated, and dynamical agents, because robustness is thought by us an others to be an intrinsic property of biological and self-organized distributed systems (see [Camazine *et al.*, 2001][Wagner, 2005][Wischmann, 2007]).

Current work on embodied, situated, and distributed cognition has rediscovered some aspects of the interaction between agents and their environments as central to the emergence of distributed cognitive processes [Ziemke *et al.*, 2004]. From a distributed cognition viewpoint, Ziemke *et al.* (2004) present some simple initial experiments that should be taken as a fruitful starting point to discuss the use of the environment to produce cognitive behaviours. Their studies mainly focus on the so-called 'road sign problem' [Thieme & Ziemke, 2002] illustrating how the evolution of environmental adaptation, at evolutionary and individual time-scales, can serve to provide cognitive scaffolding that simplifies the tasks for individual agents.

Thieme and Ziemke (2002) demonstrate that even purely reactive agents can solve the T-maze navigation task satisfactorily, where a robot should 'remember' to what side it must turn after a rightward or leftward beam of light, see Figure 3.2. The robot should move across the first corridor and then shift to one side at the junction to reach the goal (final position at right or left junction corridor). Interestingly, they observe that reactive agents (without internal states) produce

the appropriate behaviour by 'using' a wall all the way to the goal in relation to the side that the beam of light was initially presented (Figure 3.2). Agents could use their own position with respect to the wall as an external memory. Thieme and Ziemke have argued that such use of walls as environmental (external) knowledge is an example of distributed cognition sustaining behaviours.

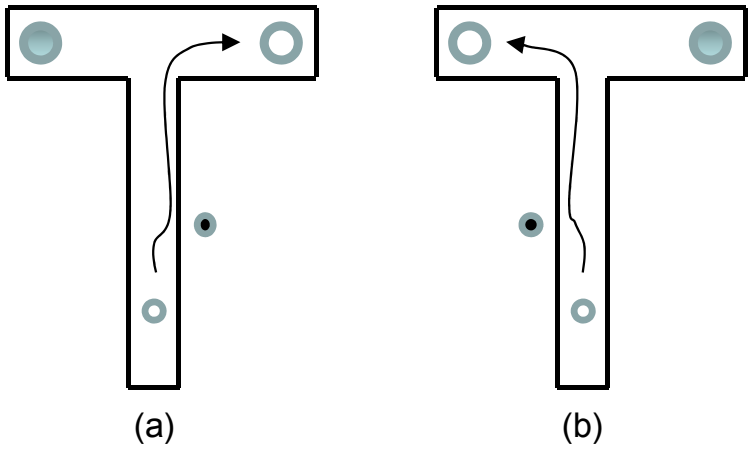

Figure 3.2 – Representation of the T-maze for a road sign problem exhibited by a purely reactive agent. The agent starts at the foot of the main corridor. The agent encounters a light source on the (a) right- or (b) left side, and after a delay period, it has to turn toward the same side at the T-maze conjunction toward the large empty circles. Agents solve this behaviour by using the respective wall all the time to the goal. Plots taken from [Ziemke *et al.*, 2004].

Ziemke *et al.*'s lessons are similar to those of [Jakobi, 1998b, Chapter 5] in experiments with a Khepera robot in a T-maze (Figure 3.3). In Jakobi's experiments, the internal controller of the robot is a neurocontroller evolved using the ER technique. Jakobi indicates that the observed behaviour involves both a behavioural control that avoids touching the sides and control that negotiates the junction at the end of the first corridor (simple reactive behaviours both), combined with the presence of an internal state for producing the appropriate turning behaviour at the junction. Ziemke *et al.* (2004, p. 340) have called this situation a delayed response task. The Jakobi's experiment is an example of how agents can exploit opportunities from the environment in order to solve a particular task under the ER methodology.

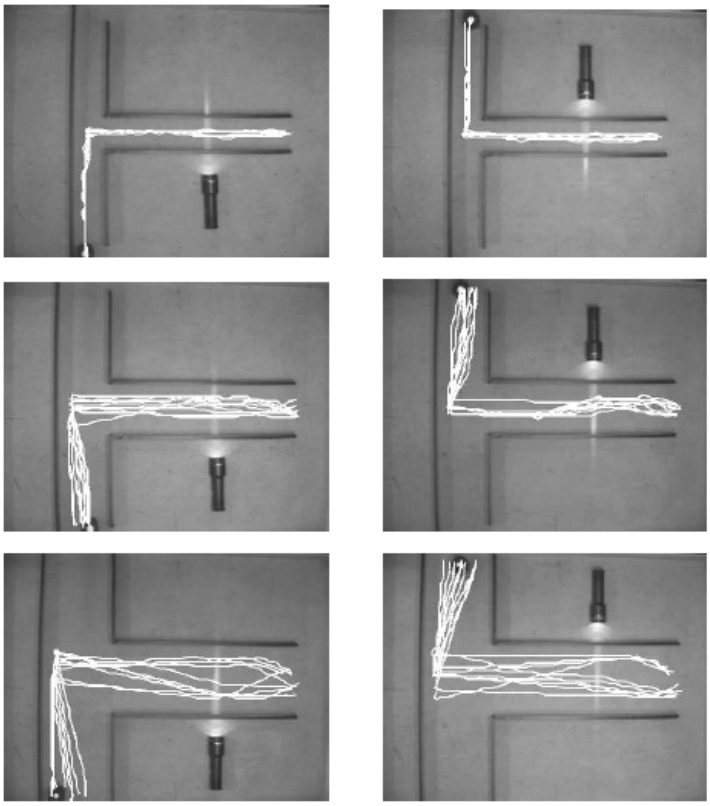

Figure 3.3 – Example of the paths taken by a Khepera robot in six consecutive trials. The robot should perform T-maze navigation considering a right- or leftward source of light. Figures taken from [Jakobi, 1998b, Chapter 5].

3.4 Final comments

A few works in adaptive systems field and ER have studied the modification and the use of the environment that agents or species (in an evolutionary sense) produce to accomplish tasks. Fewer works discuss how agents make clever use of the environment to make subsequent tasks easier, and is ripe for further explanation. This use will be seen as a modification of agent's behaviour in relation to the history of interactions with the environment (see [Nolfi, 1997, 1998] for complementary descriptions). Potential benefits include accounting for agents that overcome hardwired cognitive limitations, and agents whose cognition is distributed between internal mechanisms, external sources and, not least, the interaction between internal and external dynamics [Ziemke *et al.*, 2004]. The following chapter describes the main aspects of the ER technique that we use in our experimental chapters to evolve fit agents with distributed behavioural mechanisms. Chapter 5, Chapter 6, Chapter 7, and Chapter 8 are examples of different ways of exploiting such a distribution.

Chapter 4

Evolving minimal models in Evolutionary Robotics

"When the disturbances that threaten the organism have, over many generations, had the bi-modal form […], we may expect to find that the organism will under selection, have developed a form of fairly close to the ultrastable, in that it will have two readily distinguishable feedbacks."

W. Ross Ashby, 1960

This chapter extends initial descriptions of the methodology that we employ for synthesising agents. We introduce and discuss in some detail the ER approach (section 4.1) for evolving agents with continuous-time recurrent neural networks (section 4.3) as internal control systems. Based on evolutionary processes (section 4.2), agents with these controllers fit the requirement of the tasks for which they evolve, and exhibit robust and adaptive behaviour in tests after evolution. This chapter finishes in section 4.4 highlighting the main points of our discussions.

4.1 Evolutionary Robotics

ER is a research methodology originally attributed to Husbands and Harvey [Harvey *et al.*, 1992]. Since its proposal, ER has increased in popularity across the robotics research field, generally in the development of controllers for simulated robots [Beer & Gallagher, 1992][Cliff *et al.*, 1993] to physical ones [Nolfi *et al.*, 1994][Jakobi *et al.*, 1995][Jakobi 1998a, 1998b], amongst other areas of investigation (see [Nolfi & Floreano, 2000]). ER treats agents as dynamic systems being continuously perturbed by their environments as opposed to agents that explicitly model the world. The focus is on the emergence of adaptive behaviour and cognitive processes as we indicated in section 3.3.2 (see also [Clark, 1997][Chiel & Beer, 1997][Pfeifer & Scheier, 2001] for

complementary descriptions). The ER methodology demonstrates in a concrete way the importance of situatedness and embodiment concepts for understanding cognitive aspects of behaviour, and can be seen as giving rise to the situated and embodied dynamical systems approach [Beer, 1995a, 1996, 1997, 2003] (section 3.2).

Works in literature employing ER methodology frequently obtain agents with robust behaviour by varying (evolutionarily) the set of attributes that define nervous system (NS), body, and some environmental features affecting agent-environment coupled interactions (Figure 1.1-C). To explore robustness to certain types and magnitudes of perturbations, however, it is often necessary to generate combinational numbers of tests. To compare different systems using these tests is to analyse only a few products of many possible features (e.g. the structure of controllers) that have emerged to sustain behaviours. Small differences that perturbations produce in agent's control systems, body, or environmental dynamics may generate large differences at coupled level. Consequently, to discover the mechanisms exhibiting behaviour under *all* perturbations is probably impossible.

The problem of comparing behaviour under perturbations can be partly alleviated. Since solutions in ER are relatively assumption-free compared to other synthetic approaches [Fine *et al.*, 2007] (see also [Nolfi & Floreano, 2000] for further arguments), we can use the evolutionary approach to obtain behaviourally robust agents and then use both analytical and computational methods to compare emerged strategies under different experimental conditions. In simulated ER agents, we can usually calculate an accurate estimate of fitness (see section 2.4.1) for behavioural robustness, even when the effects of systematic perturbations are quite sensitive and non-intuitive. We start next section by introducing one common example in ER, researching on the robustness that simulated agents exhibit when transferred to physical robots.

4.1.1 Minimal models and behavioural robustness

Cliff *et al.* (1993) have suggested the importance of modelling the environment as accurately as possible to minimize the gap between simulation and reality (see also [Koch & Segev, 1989][Zagal *et al.*, 2005]). Jakobi (1998b) propose instead the 'minimal simulations approach' to overcome such a problem using simulation in ER. The main difference between Cliff *et al.*'s and Jakobi's approaches is that the former requires precise simulations models that are hard to obtain in most robotic control situations, since generally more precise simulations require greater computational resources. Jakobi's approach, however, allows the experimenter to choose which attributes of the environment should be modelled with relevance to the problem to investigate.

Minimal simulations are not only useful for crossing the reality gap, but also as a tool for investigating simple, but general behavioural properties. Jakobi *et al.*'s (1995) original minimal simulations proposal includes the careful application of environmental noise as part of the incoming signals that simulated agents should process to behave. In this respect, Seth (2000) indicates that the introduction of noise into artificially evolving systems generate positive effects in the emergence of adaptive behaviour, the facilitation of the exploration of genotype space,

and the acceleration of evolutionary search. Beer and Gallagher (1992) have used the idea of minimal simulations to study different aspects of cognition giving rise to the 'minimal cognition approach'.

Minimal simulations are simple, but not trivial. The experimenter must first divide the experimental model that will influence the exhibition of behaviour of agents into *base set aspects* and *implementation aspects* [Jakobi, 1998b]. The designer chooses this division. Only a small base set of robot-environment interactions are usually sufficient to support the expected actions of agents. These features of the simulation have a corresponding basis in reality (the base set aspects), while other features derive from the simulation's implementation (the implementation aspects) [Husbands *et al.*, 1998]. The base set aspects ideally provide relations between agent-environment that are necessary to produce the required behaviour, where evolution selects agents that successfully perform the desired behaviour if it depends only upon the base set aspects. For instance, the association between sensors and environmental stimulus (sensory inputs) should be defined in the base set aspects.

The features in the environment that affect the sensory inputs (but are 'not' required to produce a specific behaviour) represent the implementation aspects of the experiment. Implementation set aspects (e.g. the amount of sensory noise from the environment) are varied between trials to produce truly robust agents in relation to the base set conditions. The essential lesson from Jakobi's works is that an 'envelope of noise' [Jakobi, 1998a] should be placed around a simulation's base-set features so that behaviours retain their coherence in the environment. This follows from the intuition that simulation models can never be entirely accurate, but that a noise envelope compensates in a way that emulates real sensing of physical properties of an environment.

Another characteristic of minimal simulations is that *unreliability* is necessary to induce the emergence of behavioural robustness. In other words, Seth (2000, p. 79) indicates that "[Jakobi's] implementation features should be made 'extremely' unreliable through the application of very high levels of noise, so that the evolutionary search process cannot come to incorporate them in any viable controller" [Seth, 1998b, 2000] (see also [Seth, 1998a]). Some works that support Jakobi's observations are [Miglino *et al.*, 1996][Di Paolo & Harvey, 2004][Harvey *et al.*, 1996][Seth, 1998b], among others. We extend these discussions through experimental evidence including neural noise in Chapter 5.

Summarising, experiments with minimal simulations require basic features (base set aspects) that model and define behaviours. The implementation set aspects must vary allowable real world between trials much more than elements in the base set. Nevertheless, only the *right* amount of variation base-set aspects produces robust agents that transfer from simulation to physical scenarios.

4.1.2 Evolving neurocontrollers with evolutionary algorithms

One of the most successful methods for training neurocontrollers is artificial evolution using genetic algorithms (GA) (section 4.2) [Harvey *et al.*, 1992][Nolfi & Floreano, 2000]. The ER technique discussed previously has been largely promoted by faculty and students of the University of Sussex. It combines methodologies and techniques inspired by behaviour-based robotics as well as artificially evolved agents through genetic algorithms [Cliff *et al.*, 1993]. This gave rise to the Sussex approach to ER [Harvey *et al.*, 1996]. One of the main characteristics of these studies is research on minimal, embodied, situated, and dynamical agents influenced by Beer's works [Beer & Gallagher, 1992], and finally consolidated as a suitable approach [Beer, 1997]. For an extensive overview, see [Harvey *et al.*, 2005][Nolfi & Floreano, 2000][Husbands *et al.*, 1997].

One advantage of the Sussex approach is that an evolutionary algorithm does not necessarily require a behavioural or functional division in an agent's control system. This does not mean that the division in behavioural modules is not useful or certainly required in complex tasks [Togelius, 2004][Fernandez-Leon *et al.*, 2009]. Rather, such a division is not 'built-in', but may emerge via the evolutionary algorithm (EA). The feature that distinguishes the Sussex approach from other approaches is the emphasis on simple and evolutionary open strategies for robotic control. Experimenters do not propose control strategies directly because such control is probably not similar to those created when systems evolve. Hand-designed robotic control is effective for particular tasks in engineering, but builds in assumptions of the designer in how robots should solve a task (i.e. human designers after define modular components as part of a nested control system to solve a task). ER may creates, in principle, any effective design.

As it is typical in the ER literature, we evolve the weights, biases, and time constants of a given CTRNN (section 4.3.1) using a GA. Once the network parameters are determined, they remain fixed for the duration of the task (i.e. no on-line learning or synaptic plasticity takes place). Inputs are applied to the network via neuron incoming signals (I_i) to produce change in network activity. The following equation shows the integration of each node (i.e. neuron-like units) over time:

$$y^{t+1} = y^t + 0.1 \cdot \Delta y \tag{4.1}$$

The update equation of each neuron is based on Euler integration [Ascher & Petzold, 1998]. This equation integrates an internal variable y (neural activations as explained in section 4.3.1) that exponentially decays over time when incoming signals are not given. For experimental purposes, the simulation interval is generally 0.1 units of simulation (otherwise specified in each experimental chapter).

4.2 Evolutionary and genetic algorithms

A GA is an optimization technique used to find exact or approximate solutions whose defining characteristic is that it mimics the heuristic search process of natural evolution [Bäck, 1996]. GAs are categorized as global search heuristics, being a particular class of EAs [Mitchell, 1998]. The following steps (pseudo-code) describe a 'canonical' GA:

1. Randomly generate an initial population of solutions
2. Encode solutions as a population of genotypes
3. Loop until termination criterion reached:
    (a) For each genotype in population:
        i. Instantiate genotype as phenotype solution
        ii. Test solution on target problem
        iii. Assign genotype fitness based on phenotype performance
    (b) Until a new population has been filled:
        i. Choose two parents *biased* towards choosing the fitter ones
        ii. Combine parent genotypes to form child genotype
        iii. Mutate child genotype
        iv. Add child to new population
    (c) Replace old population with new population
4. Final solution is best solution from final population

Both GAs and EAs find inspiration from biological evolution: reproduction, mutation, recombination, and selection (for a detailed description of these concepts see [Bäck, 1996][Bäck *et al.*, 1997]). The traditional mutation operator, for example, relies on perturbing all genes in a *real-valued* genotype (Figure 4.1). For *binary* genotypes, the typical advice is to mutate at a rate that leads to an expected *one* bit being changed. The most common procedure to create mutations is the generation of random numbers from a Gaussian distribution; Uniform distributions, among others, can also be used [Yao & Liu, 1997].

EAs loosely mimic the mechanics of genetics and natural selection [Michalewicz & Fogel, 2004][Holland, 1975]. One of the first promoters of artificial evolution as an optimization technique was Rechenberg (1973), but GAs were initially proposed by Holland (1975) to study natural adaptation. As an optimization technique, EAs can sometimes quickly converge to optimal solutions after examining only a small fraction of the search space. An EA usually selects an initial population at random, encoded into a genotypic representation (Figure 4.1). A *fitness function* assigns a value to each member (individuals) of the population after testing it. Next, the algorithm may apply the genetic operator of crossover (i.e. controlled swapping of genes between

two members for potentially better solutions) and *mutation* (i.e. changing one gene or a set of them to provide diversity) to the population. The algorithm repeats until certain conditions are reached (for example, a pre-defined number of generations or a minimal value of fitness). The evolved solutions are not always optimal, but often represent useful compromises between constraints [Harvey *et al.*, 2005].

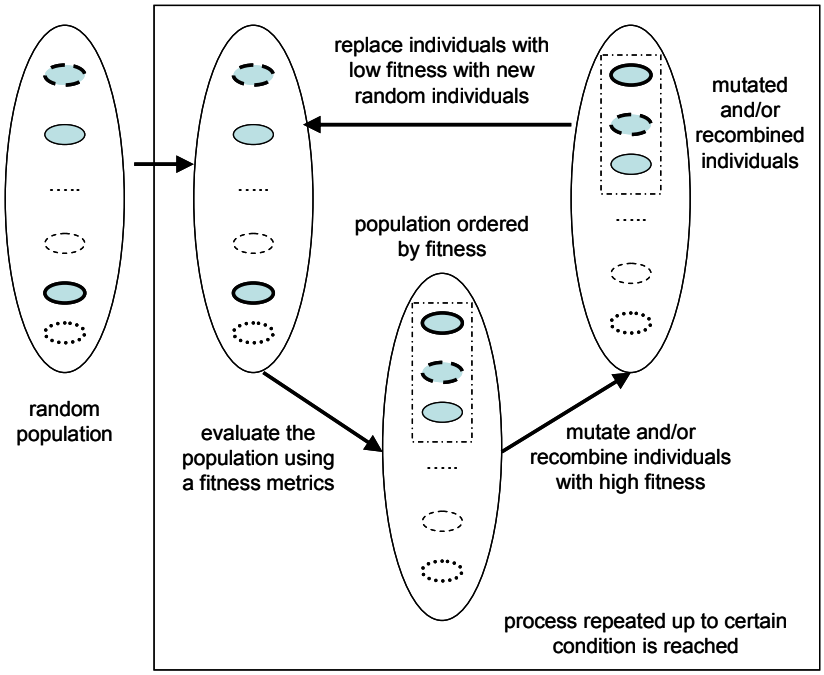

Figure 4.1 – A representation of the typical genetic algorithm process. Vertical ovals depict populations of individuals (genotypes) indicated as small horizontal ovals. One generation represents a cycle counter-clockwise. The evaluation process consists on calculating the fitness value for each individual based on the performance of phenotypes that they obtain after phenotype-environment interactions. The selection process follows a fitter score criteria. Reproduction and mutation create offspring genotypes for the next generation using variation of parents; i.e. to select parents with a *bias* towards higher fitness, but those individuals still with low fitness have some small chance to be selected in future generations. The initial population is often generated at random, and thereafter each generation increases its tendency to better population's fitness. Figure inspired and adapted from [Harvey *et al.*, 2005].

Harvey (1994, 1995, 2001) introduced the Microbial Genetic Algorithm as a GA inspired by the evolution of microbes (Figure 4.2) (see also [Harvey, 1992]). One of the main features of Harvey's algorithm is that it represents a horizontal transmission of genetic material, rather than a vertical process of evolution. Horizontal transmission of genes happens between the winners to the losers of a tournament. A *generation*, in this context, is the time that it takes to evaluate the same number of new individuals as would be in a traditional EA. We use a version of this microbial genetic algorithm in Chapter 7 and Chapter 8 where we further explain the selection of relevant parameters.

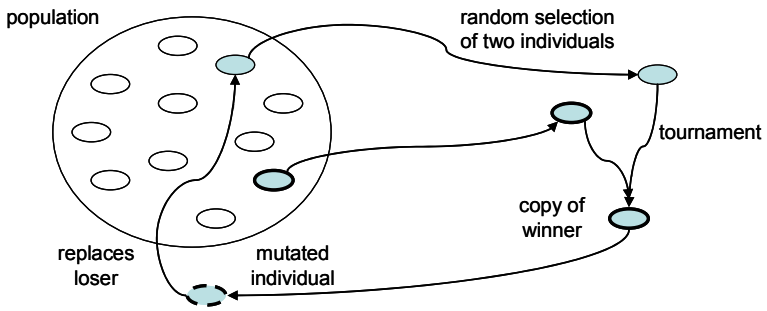

Figure 4.2 – Illustration of the Microbial Genetic Algorithm process. Figure derived from [Harvey, 1995, 2001] and [Izquierdo, 2008].

4.3 Artificial Neural Networks

Artificial neural networks (ANN) are models based on loosely bio-inspired approximations of biological networks in brains, where their elemental components are neuron-like processing elements [Haykin, 1999]. Artificial neural designers traditionally arrange these neurons in an input layer (perception neurons), a hidden layer (associative cortex) and an output layer (motor neurons) linked by synapses of varying strength. This configuration is also known as 'multilayer perceptrons' [Cybenko, 1989]. Typically, multilayer perceptrons denote feed-forward artificial networks that map sets of input data onto sets of appropriate output.

The scientific and technological community has accepted ANN [Haykin, 1999] as useful learning control techniques in autonomous mobile robotics. This is mainly because it reduces the quantity of prior design assumptions. The GA method has also been widely applied to parameter optimisation, because manual tuning of control parameters is notoriously difficult and costly in terms of time in physical robots. As an example of its use, Ram *et al.* (1994) applied GAs to the problem of goal seeking and obstacle avoidance in control mobile robots using navigation performance as a fitness measure (see also [Fernandez-Leon *et al.*, 2009]).

Commonly in ER, neural networks acting as agents' neurocontrollers are represented as a vector of numerical parameters. If the topology of the neural network is fixed, then the parameters in the genotype map directly onto the phenotypic expression of the neural network. To train neurocontrollers, we use in our experimental chapters a GA based on the ER methodology. During training, the GA continually adjusts the weights of an ANN until obtaining the desired response from the network as measured by the fitness function. This procedure is an instance of unsupervised learning; in contrast, supervised training involves supplying a set of correct responses for given inputs.

Several examples from an ER mobile robot context are available in literature using neural networks. For example, Floreano & Mondada (1996) have used a recurrent (feedback) neural network to develop a set of behaviours for a small mobile robot. They employ such a network in

navigation tasks using a corridor with sharp corners and base on a battery charger as a goal for the robot. Results show that navigation was more effective than compared to a simple Braitenberg Vehicle [Braitemberg, 1986]. Tani and Fukumura (1997) give another example via a hybrid of Kohonen and recurrent neural networks with supervised training on a physical robot with a laser range sensor and three cameras. The robot's task is to loop in figures of eight and zero in sequence, with no prior information about the environment.

These examples indicate that the use of neural networks allows flexibility to task and configuration changes. Further examples are as follows. Floreano and Urzelai (2000) have argued that neural networks only perform well if the algorithm used to fit the networks maintains the training conditions. As unpredictable environments are a common problem for physical robot navigation, they develop a more robust neural network code testing it in a small mobile robot in rectangular environments. Using conventional neural networks, and a robot able to travel to a grey area when a light was on, even slight changes in lighting affect the robot's performance. After certain adjustments, they were able to use a larger robot and arena, switching the colours and changing from a simulated to a physical one.

Yamauchi and Beer (1994) have provided another example by using a CTRNN as a control system for a robot. The task is to accomplish goal finding with the aid of a light. Sometimes the light is placed on the same side as the target and at other times, it is on the opposite side. The robot has to decide whether the light relates to the target in order to reach its goal. The control system consists of an assessment module, anti-guidance, and pro-guidance mechanisms. Following training, the robot learns to ignore the light and use other means to identify the target successfully. In the following section, we describe CTRNN as a typical neural implementation of controllers in ER.

4.3.1 Continuous-time recurrent neural networks

CTRNNs are a class of non-linear neural models that are simple but dynamically universal [Beer, 1995b][Beer, 2006]. These networks are Hopfield-based additive neural networks [Grossberg, 1988]. In general, each node in a fully connected CTRNN has n+2 parameters: a *decay constant* τ, a *bias* term θ, and n afferent connection (*synaptic weights*) from itself (w_{jj}) and from all other nodes (w_{ji}) in the network. Thus, a n-node CTRNN has $n.(n+2)$ parameters in total. Note that the space of all fully connected n-node architectures contains all n-node networks with lower connectivity. A connection weight of zero indicates a lack of connection. Since all the parameters in a CTRNN are typically real-valued, it is common to use a real-valued encoding during the evolutionary process [Nolfi & Floreano, 2000]. This is the method used in this thesis. The ranges for connection weights, bias terms, and decays are different for most of experimental chapters in this thesis. CTRNNs in our experiments are encoded into a genotype where all values are drawn from the range $[-1, 1]$ (otherwise specified for each experiment).

One of the most important arguments of using CTRNNs is that they are universal approximators of smooth dynamics [Funahashi & Nakamura, 1993]. This capacity of CTRNNs

ensures they can reach certain dynamical precision to approximate any particular given dynamics. Importantly, they are also related to biological processes like non-spiking neurons and more general dynamical models used in adaptive behaviour and minimal cognitive research [Beer, 1997, 2003]. The following equations define the implemented neuron-like units in CTRNN networks (Figure 4.3) [Beer, 1995b]:

$$\tau_i \frac{dy_i}{dt} = -y_i + \sum_j^n w_{ji} z_j + I_i \tag{4.2}$$

$$z_j = \sigma(g_j(y_j + \theta_j)) \tag{4.3}$$

$$\sigma(x) = 1/(1+e^{-x}) \tag{4.4}$$

The variable y_i is the activation of the i-th neuron (e.g. the state or 'membrane potential'); τ_i is its time constant; w_{ji} is the strength of the connection from the j-th to the i-th neuron; θ_i is a bias term; g_j is a gain; $\sigma(x)$ is the standard logistic activation function; I_i represents an external input; n is the number of neuron-like units in the network. Note that we repeat these equations in each experimental chapter for clarity.

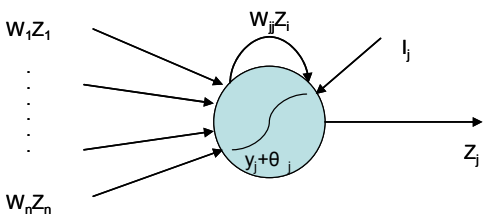

Figure 4.3 – Schematic representation of the j-th CTRNN single neuron. The neuron receives input from other neurons ($w_{ji}.z_i$), from itself ($w_{jj}.z_j$), and from an external input (I_j). The incoming signals are summed and contribute to neuron activation (y_j). Neuron firing rate (z_j) is a sigmoid function of activation (y_j) and bias (θ_j). See Equations 4.2 and 4.3.

Beer (1995b) has largely studied the dynamics of CTRNNs, and their parametrical space structure in circuits of one, two or three neurons. He has also proposed that in order to produce more dynamical sensitivity in neurons, the neuron's activation function should be centred over the full range of input that neurons receive. Beer (1995b) has studied the parameter space of CTRNNs, where he defined the following condition for center-crossing:

$$\theta_i^* = -\sum_{i=1}^{N} w_{ji}/2 \tag{4.5}$$

where θ_i stands for the bias of the *i*-th neuron and w_{ji} is the strength of the connection from the *j*-th to the *i*-th neuron. Center-crossing neurons nullcline the curves along which the activation (y_i) of each neuron is cero and intersects at the exact centre of symmetry [Mathayomchan & Beer, 2002]. Nullclines, sometimes called zero-growth isoclines, are encountered in two-dimensional systems of differential equations (see [Strogatz, 1994] for further details). When this condition is satisfied (Eq. 4.5), the null manifolds of each neuron intersect at their centres of symmetry, or, equivalently, the steady-state input-output (SSIO) of each neuron is centred over the range of synaptic inputs that it receives from other neurons [Beer, 2006]. According to Beer (2006, p. 3013):

> "Center-crossing circuits are important for a variety of reasons. First, the richest possible dynamics can be found in the neighborhood of such circuits. By 'richest possible dynamics,' I mean dynamics that makes maximal use of the available degrees of freedom in the circuit. Second, the bifurcations of the central equilibrium point of a center-crossing circuit can often be fully characterized analytically. Finally, for any given weight matrix, the corresponding center-crossing circuit serves as a symmetry point in the net input parameter space for that circuit."

Mathayomchan and Beer (2002) have found that seeding evolutionary searches with random center-crossing networks led to quicker evolution and better solutions. We use center-crossing neuron definitions in Chapter 5 where this neural restriction helps to prevent the incidence of nearly saturated dynamics that would otherwise nullify the effects of neural noise.

4.4 Final comments

The main conceptual frameworks and approaches used in this thesis are presented in this chapter and in Chapter 3. Our strategy to understand how embodied, situated, and dynamical agents exhibit behavioural robustness is by building minimal models in ER (section 4.1.1). These models enable us to test hypothesis and to formalize observations about dynamical properties of behaviourally robust agents. Our attempt is not to create realistic simple organisms, but minimal agents with robust properties. ER experiments from Chapter 5 to Chapter 8 enable us to test the appropriateness of our hypotheses by demonstrating an existence proof for behavioural robustness with the proposed experimental conditions. The simulation models also serve as instructive examples. Our models are minimal, but sufficiently complex to produce the behaviour of interest. This helps us discover features of behavioural robustness during coupling otherwise observed by domain-based complexity in the real realm.

Chapter 5

Evolving dynamically robust engagements in situated agents: a sensor-based goal-seeking task under neural perturbations

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"Natural selection insists that the nature of the parts shall be irrelevant for the behavior"

W. Ross Ashby, 1981

In literature, biological robustness is generally discussed as a by-product of evolution, where robust mechanisms emerge from noisy processes [Félix & Wagner, 2008]. This chapter explores the incidence of internally generated noise (neural noise) on agent behaviour and its effects in the production of robust traits. We evolve agents for goal seeking (phototaxis) task, testing their performance in the presence of sensorimotor and structural perturbations and for different levels of neural noise during agent lifetime. Behavioural robustness is shown to arise from coupled dynamics that shape agent behavioural mechanisms during evolution combined with dynamical features of neurocontrollers that promote robust behaviours. These agents use dynamical coupling to achieve robust behaviour. In particular, the implemented evolutionary process implicitly selects neural systems that operate in noise-resistant landscapes, which are resistant to bifurcation and/or contain bifurcations that retain phototaxis functionality. The concept of bifurcation is introduced in section 3.2.3.1, but it is further discussed in section 5.3.3 based on experiments described in this chapter. This experimental chapter also serves as a transition into the experiments of the next chapters, which continues discussions on the relation between distributed mechanisms and behavioural robustness. Here the distribution criterion refers to agent-internal-control in its

coupling with the environment. The work reported in this chapter is based on experiments in [Fernandez-Leon & Di Paolo, 2007, 2008].

5.1 Introduction

The role of noise in inner-systems with sensorimotor control is of growing interest in bio-inspired robotics – in particular, the relation of noise to agent-environment aspects of robust behaviour [Hubert *et al.*, 2009]. The understanding of the effects of neural noise on sensorimotor control is important to be extended as noise may result in movement inaccuracy (constant errors) and imprecision (variable errors and uncertainty) [Bays & Wolpert, 2007][Faisal *et al.*, 2008]. In the context of adaptive behaviour during goal-oriented tasks, Bays & Wolpert propose that the strategy of the central nervous system for dealing with neural noise, i.e. the spontaneous neural background activity present in most brain tissues, is to optimally combine sensorimotor signals. Despite this broad hypothesis, we have very little idea about how the algorithms managing of the effects of neural noise are realized at the neuronal level. The majority of work in this area neither explains how these mechanisms emerge from sensorimotor interactions, nor analyses how such strategies may have originated during evolution. In the context of artificial evolution, evidence that noise also has some useful properties has been presented several times [Jakobi, 1998a][Di Paolo & Harvey, 2004] and this leads us to a second question: whether in natural systems noise should always be considered detrimental. Combining these two ideas, the question of *what sort of control-strategy emerges if neural noise is induced during the evolution of neurocontrollers* becomes one of conceptual and practical interest not only for evolutionary and autonomous robotics, but potentially for neuroscience as well.

The use of noise is a widespread practice in ER. Applying his minimal simulations paradigm, Jakobi (1998b) has investigated the uses of environmental noise and parametrical uncertainty (rather than neural noise as in this chapter) in the evolution of neurocontrollers. He found that environmental-noise-evolved neurocontrollers have a significant rate of success when transferred from simulated agents into physical robots (where direct evolution is impractical or prohibitive). Minimal simulations work by avoiding the accurate but computationally costly replication of the physical complexities of a real-world robot-environment system. Instead, these simulations abstract a base set of factors upon which evolution must rely in order to produce the desired behaviour in simulated agents. All other factors in the robot-environment system are crudely modelled and subject to large amounts of environmental noise and variability between evaluations. The conceptual difference between Jakobi's work and experiments in this chapter is that in the former case the focus is on the efficiency of control between simulated and physical agents, while in our case we look to identify properties in agents using dynamical coupling to achieve robust behaviour.

Some of the lessons of the 'minimal methodology' may illuminate questions about natural robustness. Biological systems exhibit phenomena such as sensorimotor robustness to noise [Bays & Wolpert, 2007] or robustness in functional terms [Di Paolo & Harvey, 2004], which may relate

to the presence of neural noise and therefore warrant investigation. Studying these mechanisms in ER can inform our understanding of what to look for in natural systems and how to build better artificial examples. ER provides a useful, relatively assumption-free paradigm in which to study agent dynamics that sustain behaviours despite perturbations.

This chapter is an exploratory piece of work aimed largely at generating hypotheses, and the motivations are conceptual as well as practical. We present results from ER simulations exploring the effects of neural noise on agent dynamics in order to investigate robustness at the behavioural level. In sections 5.2 and 5.3, the methods and experiments are introduced, and in section 5.4, we examine the consequences of the results and discuss questions that remain open.

5.2 Methods

5.2.1 Agent and structure of the environment

In order to avoid unnecessary complexity, a minimal approach is deliberately used in experiments for this chapter [Jakobi, 1998b][Di Paolo & Harvey, 2004]. The aim is to evaluate the consequences of evolving networks with 'constantly changing values' of neural noise and to test the obtained solutions in terms of behavioural robustness. In this chapter, these constantly changing values are represented by a variable y_0 (uniformly distributed) where its value is randomly selected from the range [-A, A] every time step for every neuron (i.e. different neurons have different values of y_0 in each time step), where A is a fixed value for each experiment $A \in \{0,1,2,3,4\}$. The range [-A, A] of y_0 is a control parameter in our studies.

A population of simulated agents is evolved to perform light seeking (phototaxis) in normal body and environmental conditions while being disrupted by neural noise and externally induced perturbations. In each test, one light source is presented every time step for an extended period. Limited random noise is applied locally to the dynamics of each neuron.

5.2.2 Agent's controller definition

Agents are modelled as solid circular bodies of radius 5 (arbitrary units) with two diametrically opposed motors that differentially steer the agent with their output (in range [0, 1]) and two frontal light sensors positioned with a separation between sensors of 47.75°. The agents' motors can drive backwards and forwards in an unlimited 2-D arena. Agents have a very small mass, so motor neurons output directly indicate the tangential velocity at the point of the body where the motor is located. The sensors respond to the closeness of a point light source by linearly scaling the distance from the light to each sensor:

((clutteredSensorMiss).(1-(distanceToLightSource/ diagonalArena)))

The model includes sensor shadowing when an agent body occludes light. When not otherwise specified, each evaluation consists of a serial presentation of 6 light sources for a relatively long

fixed time (T_{ls}=50 time steps) during an agent's lifetime (T=300 time steps). An agent's task is to approach light sources as they appear. After T_{ls}, the light source is eliminated and another one appears at a random distance in [10, 120] and angle in range [0, 2π] degrees. The intensity of each source is fixed and equal among them. Sensory inputs are on the range [0, 1]. Distance and time units are of an arbitrary scale.

A CTRNN (section 4.3.1) controls agents. The dynamics of the network are governed by the following equations:

$$\tau_i \frac{dy_i}{dt} = -(y_i - y_0) + \sum_j^n w_{ji} z_j + I_i \tag{5.1}$$

$$z_j = \sigma(y_j + \theta_j) \tag{5.2}$$

Using terms derived from an analogy with real neurons, y_i represents the cell potential of the i^{th} neuron depending on a decaying time constant τ_i (scaled exponentially in range [1, 2+e^2]), θ_j the bias is calculated by center-crossing, z_j the firing rate, w_{ji} the strength of synaptic connection from node j to node i (range [-10, 10]), and I_i is the incoming current, which is zero for non-input nodes. CTRNNs are implemented using center-crossing [Mathayomchan & Beer, 2002] (see Eq. 4.5 in section 4.3.1). The center-crossing restriction helps to prevent the incidence of nearly saturated dynamics that would nullify the effects of neural noise. Time constants τ_i and synaptic weight w_{ji} are genetically (real-valued) encoded and optimised using a genetic algorithm.

The term y_0 (uniformly distributed) represents the level of additive neural noise as described in section 5.2.1. Even though the addition of the term y_0 could be simply considered as a perturbation on the current input (I_i), this parameter can be also interpreted as influencing the long-term behaviour of each neuron including those that receive no sensory input. The network topology consists of 2 motor neurons (#0 & #1), 2 input nodes (#2 & #3), and 2 internal neurons (#4 & #5). Full connectivity is used for linking neurons, but only output neurons include self-connections. Left/right symmetry in synaptic weights is not enforced.

5.2.3 Artificial evolution settings

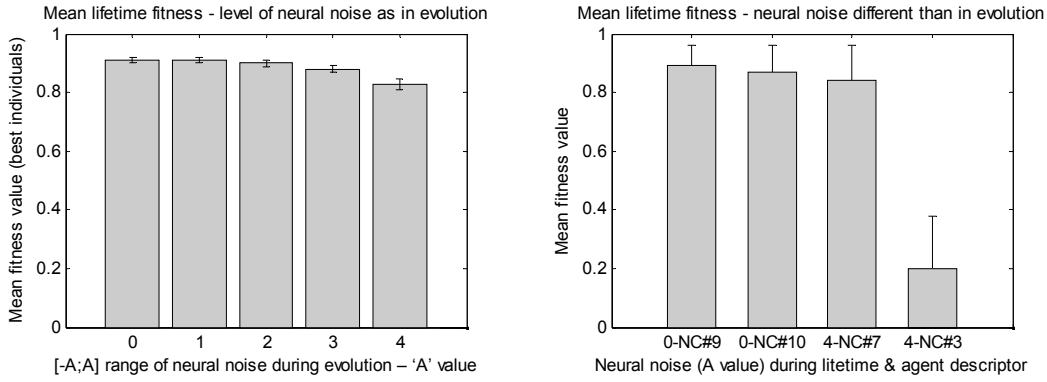
A population of 60 individuals is evolved using a steady state, rank-based genetic algorithm with elitism (50%). Each individual is run for 10 independent evaluations and the performance of each phenotype is calculated by averaging the fitness obtained in each evaluation. The mutation operator consists of the addition of a small vector displacement selected from a Gaussian distributed value in each gene (with mean 0.0 and standard deviation 1.0). When mutated genes are below or above their range, a non-reflective criterion is applied, generating a new random value for affected genes. Crossover is not used. The network and other simulation variables are integrated with an Euler time step of 0.1. Fitness is calculated in the following manner: $F = 1\text{-}D_f / D_i$, where D_f and D_i are the final and initial distance to light source for one particular

test, respectively. Fitness is determined for each light source (goal) and then averaged for 10 independent evaluations. F, in the range [0, 1], is taken as 0 if $D_f > D_i$. The genetic algorithm is run for 1000 generations and for 200 iterations per generation, generally taking a few hundred generations to achieve a high level of mean fitness.

5.3 Results

5.3.1 Statistical analysis of populations

We evolve populations with different levels of neural noise ($A \in \{0,1,2,3,4\}$) using independent random seeds, where a constantly changing value of y_0 is selected every time step in the range [-A, A] per neuron for each test. Most of evolved agents successfully acquired the capacity to perform phototaxis despite neural noise (i.e. mean performances are higher than 85% in Figure 5.1-I).



[I] [II]

Figure 5.1 – Lifetime performance in the presence of constantly changing values of neural noise (y_0), with 6 randomly positioned lights. [I] *Population analyses*. Mean fitness obtained after evolution (20 independent experiments); the x-axis is the value of A for y_0 in [-A, A]; y-axis stand for the mean lifetime fitness reached by 10 agents per data point. [II] *Individual analyses*. Comparison between selected agents evolved with A=0 or A=4 (x-axis). NC#9 and NC#10 agents were evolved with A=4 and remain with high mean fitness even when noise is removed during lifetime tests; NC#7 and NC#3 agents were evolved with A=0. For both plots, each data point represents mean fitness over 100 independent experiments per agent. Error bars indicate standard deviation.

The evolutionary process shows relatively good evolutionary fitness for agents using the described configuration of y_0 during tests. Figure 5.1-I represents mean lifetime fitness (20 independent experiments per data point) of the best 10 agents evolved for each A value (tested with 6 randomly placed light sources). This figure indicates that populations obtained with different levels of A show relative good mean fitness. In terms of robustness, agents evolved with A=0 exhibit 84.8% robustness in the presence of neural noise during lifetime ($A \in \{0,1,2,3,4\}$),

while agents evolved with A=1, A=2, A=3, and A=4 obtain 86.9%, 96.4%, 98.5%, and 99.7% respectively. These percentages specify performance under perturbations in the face of neural noise divided by the level of fitness in the control case (A=0). In the presence of sensorimotor perturbations (e.g. sensor inversion and sensors removal), mean lifetime performance is generally higher for agents evolved with A=4 than for agents evolved with lower values of A [Fernandez-Leon & Di Paolo, 2007].

Figure 5.1-II shows examples of agents obtained with A=4 and A=0 levels of neural noise during evolution:

- NC#9 and NC#10 agents evolved with A=4;
- NC#7 and NC#3 agents evolved with A=0.

In Figure 5.1-II, x-axis shows the level of neural noise used during lifetime tests, rather than representing the level of noise in evolution, where NC#i represents an agent using the i-th neurocontroller forefront. More precisely, the x-axis in Figure 5.1-II identifies the level of neural noise (A value) during lifetime and the agent descriptor for each data point (e.g. 0-NC#9 indicates that the NC#9 agent is evaluated with A=0 during lifetime tests). It is important to note that, for clarity, this chapter only provides some analysis of these four agents rather than descriptions of the whole set of agents. This is because the selected agents are representative examples of the whole set evolved with A=0 and A=4. In other words, the non-described agents have similar behaviour to the ones indicated in this chapter.

Especially, all of these selected agents demonstrate robustness to noise during lifetime when inducing the same level of neural noise than the one during evolution. Except for NC#3, a better mean fitness is also observed when inducing A=0 during lifetime for agents evolved with A=4 (0.89 for NC#9 and 0.87 for NC#10) than with agents evolved with A=0 and tested for A=4 (0.84 for NC#7 and 0.2 for NC#3). Experiments suggest that neural noise helps evolution find robust regions of the parameter space. These results and tests in [Fernandez-Leon & Di Paolo, 2007] indicate that agents evolved with A=4 remain robust to sensorimotor and structural perturbations even when neural noise is removed during tests. However, while NC#9, NC#10 and NC#7 agents maintain high levels of lifetime fitness in spite of the induced y_0 noise, NC#3 with A=4 during lifetime (Figure 5.1-II) shows low level of fitness during experiments after evolution. Understanding why some agents perform differently than others under the influence of neural noise can provide clues toward the mechanisms that deal with neural noise at neurocontroller level.

5.3.2 The agent-environment system during phototaxis task

We analyse here agents from Figure 5.1-II in order to discover the properties which allow robust performance in the presence of neural noise. The analysis focuses both on applying neural noise to single neurons and on the general effects of neural noise in neurocontrollers. The neurocontrollers of NC#9 and NC#3 agents are studied in detail because they are examples of high (NC#9; Figure

5.2-*left*) and low performance (NC#3; Figure 5.2-*right*) during tests after evolution in Figure 5.1-II (see Appendix A.1 for further details of the selected controllers). These agents demonstrate robustness or fragility, respectively, when tested with different levels of neural noise. While they represent only particular instances, understanding the difference between these neurocontrollers sheds some light on how general controllers work differently in the presence or absence of neural noise.

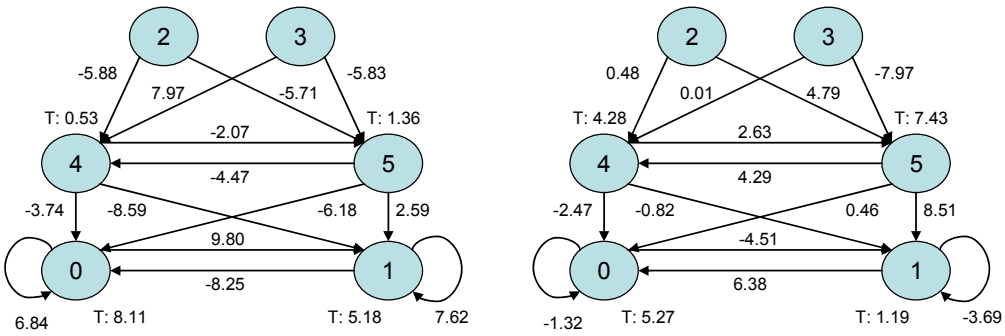


Figure 5.2 – Schematic representation of the neurocontrollers of NC#9 (*left*) and NC#3 (*right*) agents. Parameters are neuron time constant (T) for interneurons (neurons 4 and 5) and motor neurons (neurons 0 and 1), and the strength of the connection ($w(j;i)$) from the j-th to the i-th neuron (where neurons 2 and 3 represent sensors). These agents are selected for further analyses because they are representative examples of high (NC#9) and low performance (NC#3) during tests after evolution.

After studying the behaviour of agents under perturbations (see caption of Figure 5.3), we can observe that their strategies are based on maintaining light sensory inputs regardless of neural noise effects, i.e. agents regulate their movements so as to not lose the signal from light source. An intuitive description of the behaviour of agents being affected by perturbations is given as follows. When the level of neural noise is the same as the one for which agents evolved, all analysed agents (NC#9, NC#10, NC#7 and NC#3) show direct trajectories toward a light in a non-perturbed scenario (control cases). The NC#9 and NC#10 agents evolved with A=4 level of noise and tested with A=0 show movements similar to the control case or a slight right side tendency of moving toward a light, respectively. These behaviours are observed after disabling interneuron #4's activity (Figure 5.3, first row in the [1] group of plots). This simple behavioural analysis indicates that NC#9 seems to be more behaviourally robust to that sort of perturbation in comparison to NC#10. When including noise in the activity of neuron #5 (Figure 5.3, second row in the [1] group of plots), the NC#9 agent seems not to be seriously perturbed showing similar trajectories toward the light as in the control case. However, NC#10 displays a combination of slight right side moments and loops in its trajectories. We can initially conclude that NC#9 and NC#10 are affected differently under these perturbations.

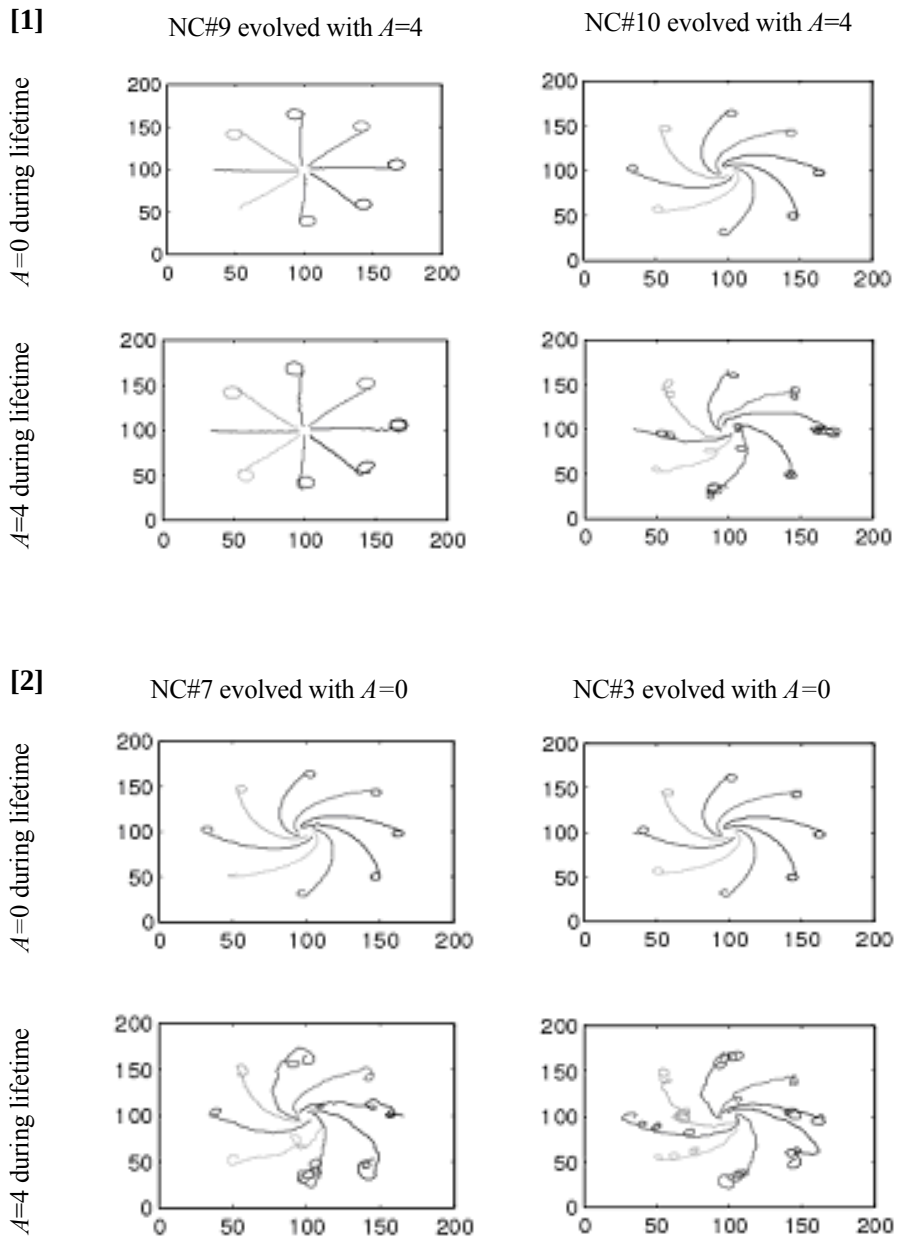


Figure 5.3 – Examples of behaviours affected by neural noise and neural disruptions. *Columns* correspond to each neurocontroller indicated at the top of the figure; each row describes the level of neural noise (*A* value) during lifetime tests. Agents start their trajectories to a light source (the small circle at the centre of each figure) from positions separated by 45° on each plot. As examples of perturbing randomly selected neurons, *top rows* of each group of plots represent behaviours in normal operation but disabling interneuron #4's activity; for each situation in the top row, *bottom rows* of each group of plots represent agent's behaviour after including noise in neuron #5 (neural noise y_0 in range [-4, 4]).

Figure 5.3 also shows that agents evolved with A=0 level of noise (NC#7 and NC#3) and tested with A=0, present a slight right side tendency of moving toward a light placed in the arena after disabling interneuron #4's activity. This behaviour is also observed when we induce noise in the activity of neuron #5 (Figure 5.3, first row in the [2] group of plots). Interestingly, these agents show a combination of slight right side moments and loops toward the light when the level of neural noise is A=4 during tests (Figure 5.3, second row in the [2] group of plots). Consequently, we can conclude from our preliminary behavioural analysis that NC#7 and NC#3 show a qualitatively different behaviour under these perturbations in comparison to the control case where perturbations are not present.

A more detailed description of how the behaviour of agents is produced and how it leads to robustness is given along the following lines. Agents in Figure 5.3 exemplify the tendency to receive sensory stimulation mainly from one side, which is evident from agent trajectories. The effects of perturbing differently two randomly selected neurons by inducing constantly changing y_0 values in range [-4, 4] in intern neuron #5 and deactivating intern neuron #4, indicate that agents can approach to light or lose the contact after turning in the 'wrong direction' (i.e. avoiding light contact); and thus producing movements to sense it again (Figure 5.3). These types of perturbations are commonly employed in perturbation analysis in neural-like system (see [Keinan, 2005]). This observation suggests two different modes of maintaining light contact: from right or left side. Analysing the lasting response of neurocontrollers when sensory inputs are forced to be constantly activated or deactivated can show in more detail how different behavioural responses are generated in the presence of neural noise. Because the noise term y_0 in Eq. 5.1 is additive, nullclines in phase space will tend to be relatively displaced to each other for different values of y_0, but not warped or changed (as would be expected if noise were added to a weight term) [Beer, 1995b]. It is worth noting that nullclines are the geometric shape for which a differential equation is equal to 0, and that the fixed points of the system are located where all the nullclines intersect [Strogatz, 1994].

Table 5.1 shows the long-term responses of NC#9 and NC#3 as the difference between left and right motor neuron activities (i.e. neuron #0's and neuron #1's output activations). This difference produces leftward and rightward movements for phototaxis behaviour. To achieve these results, we force incomings to be constantly activated (sensor inputs=1) or deactivated (sensor inputs=0) given fixed values of $y_0 \in \{-4, 0, 4\}$ in neurons #4 and #5, with y_0=0 for the remaining neurons. A positive difference means that an agent turns left, while a negative difference implies an agent or eventually turns right. The lasting response of neurocontrollers for each sensor and fixed y_0 configuration helps to differentiate the neurocontrollers' strategies for approaching a light source as noted in Figure 5.3. We explain as follows the approaching strategy of NC#9, but a similar analysis holds for NC#3 based on Table 5.1.

Our categorization of all behavioural space divides into rightward and leftward movements of agents without taking into account the magnitude motor output responses in Table 5.1. This two-valued categorization is because, by definition, a qualitative change in behaviour usually implies a change in associated dynamics. In our experiments, the strategies for right or left side approaching

are exhibited during negative or positive motor responses, respectively. In this case, we are interested in identifying these changes in direction, because a change of magnitude in motor output do not necessarily entail a qualitative change in right or left approaching behaviour.

input neurons		**neural noise interneurons**		**motor response**	
#2	**#3**	***y_0* #4**	***y_0* #5**	**NC#9**	**NC#3**
0	0	-4	-4	0.103 (←)	0.200 (←)
0	0	-4	0	0.170 (←)	0.102 (←)
0	0	-4	4	0.211 (←)	-0.019 (→)
0	***0***	***0***	***-4***	-0.114 (→)	***0.205 (←)***
0	***0***	***0***	***0***	***-0.094 (→)***	***0.108 (←)***
0	0	0	4	-0.041 (→)	-0.012 (→)
0	0	4	-4	-0.116 (→)	0.210 (←)
0	0	4	0	-0.100 (→)	0.114 (←)
0	0	4	4	-0.075 (→)	-0.005 (→)
1	1	-4	-4	0.214 (←)	0.065 (←)
1	1	-4	0	0.233 (←)	-0.060 (→)
1	1	-4	4	0.242 (←)	-0.175 (→)
1	1	0	-4	0.214 (←)	0.071 (←)
1	1	0	0	0.233 (←)	-0.053 (→)
1	1	0	4	0.242 (←)	-0.168 (→)
1	1	4	-4	0.214 (←)	0.077 (←)
1	1	4	0	0.233 (←)	-0.046 (→)
1	1	4	4	0.242 (←)	-0.162 (→)

input neurons		**neural noise interneurons**		**motor response**	
#2	**#3**	***y_0* #4**	***y_0* #5**	**NC#9**	**NC#3**
0	1	-4	-4	0.172 (←)	0.249 (←)
0	1	-4	0	0.202 (←)	0.171 (←)
0	1	-4	4	0.226 (←)	0.064 (←)
0	***1***	***0***	***-4***	0.160 (←)	***0.253 (←)***
0	***1***	***0***	***0***	***0.199 (←)***	0.176 (←)
0	1	0	4	0.225 (←)	0.070 (←)
0	1	4	-4	-0.099 (→)	0.258 (←)
0	***1***	***4***	***0***	***-0.043 (→)***	0.182 (←)
0	***1***	***4***	***4***	***0.128 (←)***	0.076 (←)
1	0	-4	-4	0.200 (←)	-0.018 (→)
1	0	-4	0	0.225 (←)	-0.139 (→)
1	0	-4	4	0.238 (←)	-0.236 (→)
1	***0***	***0***	***-4***	0.200 (←)	***-0.011 (→)***
1	***0***	***0***	***0***	0.225 (←)	***-0.133 (→)***
1	0	0	4	0.238 (←)	-0.230 (→)
1	0	4	-4	0.192 (←)	-0.004 (→)
1	***0***	***4***	***0***	***0.223 (←)***	-0.126 (→)
1	0	4	4	0.237 (←)	-0.225 (→)

Table 5.1. Long-term responses of NC#9's and NC#3's turning behaviours. Table shows the difference between left and right motor activities (motor response), when sensory input nodes #2 and #3 are forced to be constantly activated (sensor input=1) or deactivated (sensor input=0) (indicated for each response data); y_0 #4 and y_0 #5 represent fixed levels of neural perturbation ($y_0 \in \{-4, 0, 4\}$) in interneurons #4 and #5, respectively. Arrows indicate rightward (→) or leftward movements (←). Highlighted (bold-italic) rows are referred to in the main text.

We start our analysis of NC#9 with no lights (sensor inputs=0) and without noise in any neuron. In this situation, the agent moves slightly turning right due to motor response -0.094 (indicated as (0;0;0;0) for (#2; #3; y_0#4; y_0#5) in Table 5.1). This motion will cause that right sensor to encounter the light. Then, the right sensor will start to receive more input, causing the agent to turn left slightly when approaching the light due to motor response 0.199 (indicated for (0;1;0;0) values of (#2; #3; y_0#4; y_0#5) in Table 5.1). This produces a decrease of the right sensing input up to the non-sensing situation as in the starting case, because the sensor loses contact with the light. After approaching the light blindly, the agent will generate a new movement to right (similar to that described before), generating again an increase of the right input sensing.

From a long-term perspective, this right strategy will cause the right sensor activity to be increased or decreased depending on robot's approach to light. However, in normal phototaxis, values of y_0 change, which can produce a change in the approaching strategy of NC#9 toward a left sensor configuration (see for example (4;0) or (4;4) values of (y_0#4; y_0#5) in Table 5.1). In this

case, starting from the situation sensing no light, eventually the right sensor will perceive first more light than the left sensor, producing agent motion to the right (motor response -0.043); or slight moves left (motor response 0.128) for (4;0) and (4;4) values of (y_0#4; y_0#5), respectively (Table 5.1). When the levels of y_0 are (4;0) for neurons (y_0#4; y_0#5), the agent will move to produce a decrease in right sensor input due to the approaching angle to the light. The left sensor input will increase generating a left movement (motor response 0.223) instead of a right movement, as explained before for the right sensor configuration. A similar strategy using the left sensor is observed with (4;4) levels of (y_0#4; y_0#5), but control takes longer, i.e. the robot turns left more slightly when the right sensor input increases during the approaching behaviour. We conclude that the strategy of NC#9 for maintaining phototaxis behaviour with left or right sensors is based on the combination of internally generated motor responses and agent's situatedness, which creates the approaching behaviour that eventually activates right or left sensors as described previously.

5.3.3 The effect of perturbations in a dynamically engaged system

The phototactic behaviour is not demonstrated in other configuration of noise during a normal sensing approach. For example, adding y_0=-4 to neuron #4, regardless of the level of noise in neuron #5, results in the agent not performing phototaxis because to agent loses the capacity to turn right and also the ability to maintain right or left sensory inputs (see Table 5.1). Similarly, setting y_0=-4 in neuron #5 and y_0=4 in neuron #4 also produces non-phototactic behaviour, because left movements are not reached correctly during normal sensing approach. This observation is important because we realize that the NC#9 agent falls into a left or right sensor configuration depending on the value of y_0 in the interneurons *and* current sensing.

Let us now look at NC#3 with no input sensing (agent sees no lights) and without neural noise. This agent turns left (motor response 0.108 indicated for (0;0) values of (y_0#4; y_0#5) in Table 5.1). Eventually, the left sensor will activate abruptly, producing a rightward movement (motor response -0.133) that will generate a decrease in left sensor input when the agent approaches light. This use of the left sensor is also observed during normal sensing situations when the level of noise in internal neurons is (-4;0) and (4;0) values of (y_0#4; y_0#5). Phototaxis is performed only in non-noisy configurations, because the agent loses its capacity for turning left using its left sensor. For example, in (0;-4) of (y_0#4; y_0#5) configuration, the NC#3 agent turns left (motor response 0.205) when it senses no lights, which eventually will produce an increase of left sensing and a slight right movement (motor response -0.011). However, this right movement is not enough to maintain left sensory input while the agent approaches a light. This means that eventually the right sensor becomes activated, producing a left movement (motor response 0.253), which results in a new non-sensing situation with both sensors. According to the lasting response of NC#3 in Table 5.1, the agent sometimes turns in diverse directions with different levels of noise mainly when both sensors are activated or when no sensing is produced. The agent will receive overall inputs from 'the wrong side', causing movements that do not approach a light. This long-term analysis

however only provides an indication of how the attractor landscape is affected for different configurations of sensory input and y_0 values of neural noise.

Based on Table 5.1, our observations of the actual phototaxis indicate that NC#9 performs well in 5 out of 9 cases ((0;0), (0;-4), (0;4), (4;0), and (4;4) values of y_0 in neurons #4 and #5). NC#3 however produces 3 out of 9 ((0;0), (-4;0), and (4;0) values of (y_0#4; y_0#5)). Moreover, NC#9 is able to deploy at least two different behavioural strategies (section 5.3.2) while only one has been observed for NC#3. By taking the values of y_0 investigated as rough representatives of the whole space of variation for y_0, we can conclude that for most levels of noise (but not all) NC#9 will perform phototaxis using a combination of two strategies, though that this is not the case for NC#3. NC#9 is therefore sometimes undergoing bifurcations at phase space level (section 3.2.3.1), but they are most of the time functional allowing it still to perform phototaxis (roughly around two-thirds of the time). Nevertheless, about one third of the time these bifurcations are non-functional, as described before. For example, NC#9 is not significantly affected by noise when sensors are simultaneously activated, but it generates wrong long-term responses (turning left instead of turning right, for example) more frequently than in NC#3 where input sensors are deactivated simultaneously depending on the levels of noise. However, noise produces dysfunctional bifurcations in NC#3's neurocontroller dynamics more frequently than in NC#9. Again, as specified in section 3.2.3.1, a bifurcation occurs when a small smooth change made to the parameter values of a system (the bifurcation parameters) causes a sudden qualitative or topological change in system behaviour [Blanchard *et al.*, 2006].

The proposed general hypothesis is that *those controllers evolved with enough noise undergo fewer long-term dysfunctional bifurcations because of noise*. Evolution finds networks that operate in regions of phase space for which moderate displacement of the nullclines does not significantly affect the functionality of the inner-system. NC#9 has two different strategies for approaching light in the presence of noise, this implies that noise can generate bifurcations at phase space but they happen to be also functional. For perturbations in the noise range, perturbations do not usually cause qualitative changes to inner-system functionality. Evolution is therefore not only searching for regions of parameter space where bifurcations in phase space induced by noise are unlikely to happen, but also for regions in phase space where 'neighbouring' bifurcations are also functional during agents' lifetime.

Analysis in this section suggests that NC#9 produces sharp changes in its behaviour. However, there are still three possibilities to explain how fitness is maintained high despite neural noise:

- *(I)* those particular bifurcations do not largely affect the transient dynamics of the network;
- *(II)* all (or most) bifurcations produce different forms of instantaneous phototaxis (they are mostly functional in themselves);
- *(III)* no bifurcations are produced.

The last possibility (*III*) is not considered for further discussion in this chapter because it refers to the absence of bifurcations at neurocontroller level, and we have given evidence of the existence

of long-term bifurcations during agents' coupling (section 5.3.2). The two first possibilities also imply two explanations:

(1) negative (non-functional) bifurcation may indeed happen in the range of the noise parameter, but these bifurcations may be short lived while the agent performs phototaxis;
(2) negative (non-functional) bifurcation may occur for significant amounts of time, creating bifurcations that lead asymptotically to non-phototaxis.

In the first case (1), bifurcation during an internal transient seems to be related with NC#9 because robustness against noise is functionally maintained despite increasing neural noise in most situations. The agent still performs phototaxis because it is held in a transient between attractors that are functional (see [Iizuka & Di Paolo, 2007a] and experiments in Chapter 8). By contrast, NC#3 probably corresponds to case (2) with noise leading to the loss of performance when it is increased. We have not ruled out internal transient effects for the situation described for NC#9, however.

5.4 Discussion: the relation between situatedness and internal dynamics for robust behaviour

Experiments with neural noise have been presented in this chapter from an evolutionary and sensorimotor perspective. The simulation model in itself is minimal but results suggest that, at least experimentally, evolution relies on behavioural mechanisms that maintain functional (coupled) dynamics in inner-transients, as shown for the NC#9 agent. Results also indicate that neurocontrollers lose sensitivity to detrimental effects of noise when internal-systems (neurocontrollers) are evolved with high levels of neural noise (i.e. $y_0 \in [-4, 4]$).

From an evolutionary perspective, the interesting lesson is that *neural noise in evolution seems to put pressure for selecting neural systems that are resistant to non-functional bifurcation in phase space*, and so robustness lies in having a dynamic landscape that remains, in the overall balance, functionally the same during behaviour. This is evidenced by the noise robustness of NC#9 and the noise sensitivity of NC#3. The relationship between behavioural mechanisms emerging from evolution with neural noise has been minimally investigated in the simulation studies so far. In fact, mechanisms where noise is irrelevant could vary from the simple attractors' view where noise utility is removed because of convergence to stable system dynamics.

Our results suggest that the evolutionary process in the presence of neural noise – following the logic of Jakobi's minimal simulations – is finding robust neural dynamics that, when coupled with the environment, produce phototaxis. However, this robustness has a structure. It is a combination of locating the evolved neurocontrollers in regions of parameter space that maximize evolutionary fitness which bases on lifetime fitness of agents and, if and when bifurcations occur in phase space

(or are unlikely to occur), agents remain in balance functional showing phototaxis. This finding suggests that robustness to other sensorimotor perturbations may be a by-product of locating such regions of parameter space, which refers to the evolutionary history of how an evolved population goes through successive generations. If this is so, a prediction from this result is that a similar evolutionary process under parametrical variability (e.g. neural noise), but applied to non-additive parameters (such as weight synaptic values) may result in even higher levels of robustness to sensorimotor perturbations.

In our results, and in accordance to the above explanation, good performance was also observed when noise was removed, indicating that noise is *not* actively maintaining functionality in the analysed neurocontrollers. Nevertheless, we do not discard the idea that evolution may find neurocontrollers for which noise is advantageous, in which case our explanation will need to be appropriately modified. Such last idea is further investigated in Chapter 7 and Chapter 8, including comparisons using embodied agents to perform qualitatively different tasks.

Chapter 6

Evolving cognitive-behavioural dependencies in situated agents: a minimal cognitive categorization task with dynamically limited agents

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"... when a constraint exists advantage can usually be taken of it."

W. Ross Ashby, 1956, p. 130.

In Chapter 5 we have discussed how agents develop coupled engagements and use neurocontroller properties to sustain behaviours in the presence of internally induced perturbations (i.e. neural noise). This chapter continues investigating the emergence of behavioural mechanisms but evolves agents with dynamically limited controllers (monostable agents) and compares them to less limited ones (bistable agents). 'Dynamically limited' here relates to a reduced quantity of steady states that an agent controller exhibits when it does not receive stimulus from the environment. As indicated in section 1.3, again, neurocontrollers showing long-term global stability around one fixed-point are named as monostable controllers in this chapter; while those controllers exhibiting two fixed-point attractors within the intrinsic dynamics of analysed successful agents are referred to as bistable (see further descriptions in section 6.4.2). Agents are evolved for categorical perception, a minimal cognitive task [Beer, 2003], and must correlate approaching or avoiding movements to different types of objects in the environment. The model has been designed so that the final input state of agents is qualitatively the same for both approaching and avoiding behaviours, i.e. without sensory stimuli from the environment. In this way, we challenge evolution to exploit opportunities in brain-body-environment coupled dynamics, given a restricted amount of internal dynamical resources.

Results suggest a small but significant tendency of better performance by monostable in contrast to bistable agents in the presence of sensorimotor, structural, and mutational perturbations. We argue that the difference is based on greater environmental dependence of neurocontrollers to coupled dynamics. We also extensively analyse the behaviour and engaged dynamics of best-fit agents. However, as mentioned before, results are partial but not definitive because of such slight tendency. This chapter lays the foundation for further experimental work inducing coupled (environmental or body-based) dependencies of behavioural mechanisms in next chapters. Here the distribution criterion refers to the use of external factors for behaviours, where environmental dependence is induced via limited neurocontroller dynamics. This chapter is derived from work submitted for journal publication (see [Fernandez-Leon, sub. 2010a]).

6.1 Introduction

Studies in systems biology show that bacteria reach extreme robustness under harsh stress conditions [Balaban *et al.*, 2004][Alon, 2006][Alon *et al.*, 1999]. It is assumed that bacteria can reach robustness by creating internal switches from one steady state to another to keep themselves functional, rather than trying to sustain a given state [Kitano, 2004a]. In such a dynamical interpretation, however, the roles of body (embodiment) [Ziemke, 2003] and spatio-temporal factors (situatedness) [Brooks, 1991d] are not considered despite the fact that bacteria are free moving organisms.

Work here reinforces the idea given in previous chapters that behavioural robustness may well turn out to be a property of a particular organism-internal-control in its *coupling* with the environment, rather than a systemic property that is 'ensured from inside' (a common interpretation in current systems biology [Kitano, 2004a]). This research aims to understand both (*i*) whether feedback from the actions that an agent produces in the environment is a decisive factor underlying behavioural robustness, and (*ii*) whether further dynamical complexity at neurocontroller level helps the emergence of robust behaviour. Without this feedback, it can be hypothesized that an agent will more easily be driven by perturbations to internal states that do not correlate with current environmental situations, and as such, it will produce non-appropriated categorical perception.

For (ii), research in adaptive systems raises the question whether agents with further dynamical complexity at internal control can better cope with perturbations than dynamically simpler agents. In the former agents, internal dynamics could ideally transit between dynamical states, enabling agents to cope with the effects of perturbations [Kitano, 2007]. In the latter agents, for instance, internal control could be rooted in transient dynamics around one attractor (internal state) [Buckley *et al.*, 2008][Fine *et al.*, 2007]. Answers to question (*ii*) have a conceptual and practical interest for ethology and theoretical biology [Cliff, 1991], because they will provide a broad account of the simple dynamics and mechanisms underlying robustness (see [Hobbs *et al.*, 1996][Teo, 2004]). In fact, as we indicated in Chapter 3, robustness studies have *not* typically

been addressed from the point of view of coupled dynamics [Silverman & Ikegami, 2010]. Towards this aim, this part of the thesis describes statistical, behavioural and dynamical analyses to answer questions (*i*) and (*ii*).

Work here contributes to this approach (coupled dynamics for robust behaviour) with experimental proofs and discussions from a computational perspective. The ER technique (Chapter 4) is used to give the right conditions during evolution for the emergence of dynamically limited control systems performing *categorical perception* [Slocum *et al.*, 2000][Williams *et al.*, 2008]. Experiments in this chapter induce the emergence of agents that cannot exclusively rely on internal control for robust and adaptive behaviour, but they can exploit agent-environment coupling for the categorization task.

The next section introduces related works. The methods and experimental configurations are given in section 6.3. Section 6.4 and section 6.5 examine the results obtained and provide discussions to validate the hypothesis described.

6.2 Related works

The use that agents show of environmental dynamics can be investigated via small bio-inspired models. For example, Thieme and Ziemke (2002) describe agents showing T-maze navigation by using walls all the way toward a goal (section 3.3.2). The decision for turning to one side rather than another depends on a beam of light initially given by the experimenter. They argue that such use of walls is an example of *distributed cognition* to perform T-maze goal approaching; that is, the dependence on external conditions can be seen as part of a control strategy which is distributed among internal-control, body, and environment [Thieme & Ziemke, 2002]. Thieme and Ziemke indicate that an agent's own position regarding a wall represents a simplified external memory that overcomes the absence of internal memory states. Hutchins (1995) gives similar arguments about the use of the external world, suggesting that the role of material environment is part of an agent's cognitive strategy to produce behaviours.

Discussions in this chapter exemplify the use of coupled dynamics for robust and adaptive behaviours in a task that raises issues of genuine cognitive interest (i.e. categorical perception in minimal agents) [Beer, 1996]. After making a preliminary investigation of the difference between agents with one or two internal (dynamical) states, this work goes on to consider the engagements of internal-control, body and environment that agents exploit to produce approaching and avoiding behaviours. The following section describes the methods used for this research.

6.3 Methods

6.3.1 Agent and structure of the environment

The categorical perception task presented here is defined mostly following descriptions given in [Slocum *et al.*, 2000] and [Williams *et al.*, 2008]. However, the task is implemented by evolving agents with binary (rather than continuous) sensors. This is made to simplify the analysis of non-linear dynamics during behaviours. Such a simplification creates a reduction of the number of sensory states (7-sensor signals) in every time step. Note that it is not required for evolving a categorical perception task to have agents with continuous sensors. This work also defines variations on the internal agent architecture and object configuration, which differ from the settings given in [Williams *et al.*, 2008]. Here 5 rather than 3 interneurons are used (further discussed in section 6.4).

Following the same line of investigation in minimal cognition as in [Beer, 1996], the implemented task requires the capacity of agents to differentiate between 'objects to approach' and 'objects to avoid'. Categorization here depends, however, on sensing two diamonds that are (*i*) *separated enough* ($d \neq 0$, with $d >$ agent's body diameter) to enable the agent body to pass through the diamonds, or (*ii*) *close enough* ($d=1$) where there are no chances for the agent to accommodate its body between the diamonds (Figure 6.1). An object of each type is dropped from 21 different starting positions, and this is repeated 3 times for each object. This gives a number of 63 trials per type of object to profile the ability of an agent for categorical perception. *Trials* represent the number of times the simulation drops an object.

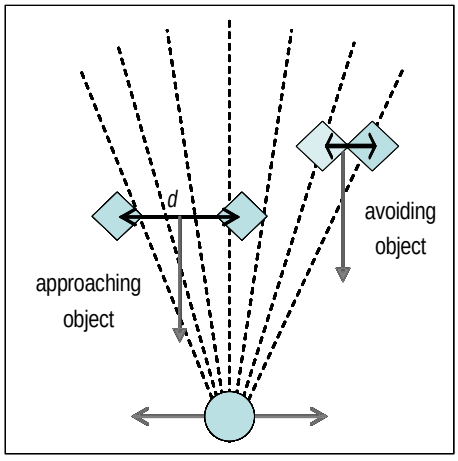


Figure 6.1 - Experimental setup for the categorical perception task. The agent (circle) can move horizontally while objects composed by two diamonds with an adjustable aperture *d* fall from above.

An agent is placed at the centre, in the bottom part of the arena (horizontal axis), and objects are initially located at the top part in the range [-100, 100] (arbitrary units), relative to the agent's initial position (Figure 6.1). In each trial, the state of every unit in the agent's internal control (neurons) is initialized to zero. Objects fall down from above to lower positions where the agent moves horizontally (the bottom part in Figure 6.1). The final agent-object horizontal distance describes approaching or avoiding behaviours.

In a more 'traditional implementation' of categorical perception [Beer, 2003] (i.e. with squares [Slocum *et al.*, 2000] and circles [Williams *et al.*, 2008] to categorize), the final state of the agent's sensors is all activated for approaching, while sensing nothing for avoiding behaviour. The layout of objects used in this chapter (two falling diamonds), challenges the evolutionary process in that the final state of the agent is the same for approaching and avoiding tasks (i.e., without external sensory stimulus). In this way, we induce that agent's neurocontrollers do not develop different dynamical states for approaching and avoiding tasks because of these final sensory states. This last point is further discussed in section 6.3.4 in relation to the emergence of monostable controllers.

6.3.2 Agent's controller definition

The following experimental settings are chiefly based on descriptions given in [Beer, 2003]. The agent model has a circular body with a diameter of 30 (arbitrary units) receiving stimulus from an array of seven sensor rays (maximum length 325 arbitrary units) that are equally placed from the centre of the agent over an angle of $\pi/4$ on the agent's top side (Figure 6.1). Sensors take binary values representing the intersection (incoming signal 1) and no-intersection (incoming signal 0) between a ray and an object. A continuous-time recurrent neural network (CTRNN) [Beer, 1995b] controls the behaviour of an agent. The intersection between object and ray causes a binary signal that is processed by the corresponding sensory node and transmitted to 5 interneurons. Interneurons connect to 2 motor neurons that control the horizontal displacement of an agent (i.e. difference in neurons z_j values according to Eq. 6.2). The following equations define the implemented neuron-like units:

$$\tau_i \frac{dy_i}{dt} = -y_i + \sum_j^n w_{ji} z_j + I_i \tag{6.1}$$

$$z_j = \sigma(g_j(y_j + \theta_j)) \tag{6.2}$$

$$\sigma(x) = 1/(1+e^{-x}) \tag{6.3}$$

where y_i is the activation (the state) of the i-th neuron, τ_i is its time constant in range [1, 2], and w_{ji} is the strength of the connection from the j-th to the i-th neuron in range [-5, 5]; θ_j is a bias term in range [-10, 0] for input nodes and [-5, 5] for interneurons; g_j is a gain in range [0, 10] for input nodes and [-5, 5] for interneurons; $\sigma(x)$ is the standard logistic activation function; I_i represents an external input (from a sensor), and n is the number of neurons in the network. Neuron activations

are calculated forward through time by straightforward time-slicing using Euler integration with a time-step of 0.1. The neuron's activations are re-initialized between different trials to zero y_i activation.

The network architecture is defined as bilaterally symmetric in the connection weights, biases, and time constants. While imposing such symmetry often made trials involving nearly centred objects difficult, it reflects the symmetry of the agent and the task, and halves the number of parameters to evolve. All the sensory nodes share the same time-constant with value 1, while bias and gain parameters for sensors, bias, gain, and time-constant for internal and motor neurons, and synaptic connections are genetically determined.

6.3.3 Artificial evolution settings

A real-valued genetic algorithm [Mitchell, 1998] is implemented to evolve the CTRNN parameters. The 51 parameters are encoded on a vector of real numbers in the range [-5, 5]. The evolutionary process works using a population size of 300 neurocontrollers. Initially, a population of genotypes (neurocontrollers) is established assigning random values for each evolving parameter. The genetic algorithm selects a specified elitist fraction of 100 top individuals in every generation using a rank proportionate criterion, which are copied to a new population in the next evolutionary generation (1000 generations in total). The remaining 200 individuals are determined using both mutation and crossover over the elitism fraction.

The evolutionary crossover method creates an offspring from two genotypes derived from recombination with probability of 0.2 (single point crossover). Following descriptions in [Beer, 1996], vector mutation is applied by adding to the genotype a random displacement vector whose direction is uniformly distributed on the M-dimensional hypersphere. The magnitude of this vector is a Gaussian random variable with 0 mean and variance 0.05. This variance has reported a good evolutionary convergence of fitness in our preliminary tests (experiments non-reported here). Finally, muted genes are linearly mapped to every evolutionary parameter in their phenotypic scales.

The performance of each agent is maximized by averaging the fitness obtained in the whole set of trials for avoiding and approaching objects simultaneously. Eq. 6.4 describes the proposed fitness measure that discriminates between an aperture wide enough for the agent to pass through (approaching objects) and a zero aperture (avoiding objects). The final horizontal separation s_i between the centre of the agent and the object is obtained at the end of the i-th trial. This fitness measure assigns near-zero value to incorrect actions and linearly penalizes by misses. Since making the correct decision without hitting the diamonds results in a significantly higher score, this measure also rewards accuracy in agent's movements in a similar way than developed in [Slocum *et al.*, 2000].

$$f = \sum_{i=1}^{n} p_i \Big/ n \tag{6.4}$$

$$p_i = \min\left(100, \quad a \cdot |s_i|\right) \qquad \text{if avoiding} \tag{6.5}$$

$$p_i = \max\left(0, \quad 100 - b \cdot |s_i|\right) \qquad \text{if approaching} \tag{6.6}$$

The implemented algorithm determines the fitness for a trial (n trials in total) considering the absolute horizontal distance ($|s_i|$) between the centre of an agent and the falling object. Fitness is measured when the object is at a random distance in range [0, 10] (arbitrary units) from the agent's final (vertical) position. In this way, it is prevented that evolution comes up with agents that approach or avoid objects predominantly at the end of a trial. The s_i distance is multiplied by an adjustment constant a or b, for avoiding or approaching objects, respectively (further explained below). The algorithm clips the obtained fitness measure to a maximum value of 100 units (see Eq. 6.5 and Eq. 6.6) and then normalized in range [0, 1]. A final separation between the agent and object of zero corresponds to a perfect approach, and a maximum separation (defined by 100 units in Eq. 6.5 and Eq. 6.6) represents a perfect avoidance. More evaluations (20) in the last generation are used to better profiling the performance of agents. That is, 20 times a particular object is leaved to fall down from a different position in the arena (section 6.3.1), and for each time fitness is independently measured and finally averaged.

6.3.4 Inducing monostable and bistable network dynamics

This section describes the developed process to induce mono- and bi-stability via evolution. Initially, the reader should be aware that at least two different strategies can be used for this purpose: *strategy 1* to impose explicit dynamical constraints at neural dynamics level, or *strategy 2* to define experimental conditions that require different modes of behaviour. The following descriptions clarify these strategies to support methodological aspects for this chapter.

Buckley *et al.* (2008) give an example of *strategy 1* for inducing monostability in the autonomous dynamics of neurocontrollers (i.e. in the absence of incoming signals). They discuss how to obtain monostable controllers based on explicit restrictions in the dynamics of agents evolving for a goal-approaching (phototaxis) task. Firstly, they require center-crossing in the network configuration. The effect of defining center-crossing neurons is that it nullclines the curve along which y_i=0 (see Eq. 6.1) intersects the exact centres of symmetry of each neuron [Mathayomchan & Beer, 2002]. Buckley *et al.* obtain local stability in CTRNNs as a necessary, but not sufficient precondition for global stability of the full, nonlinear center-crossing system [Buckley *et al.*, 2008, p. 106]. Secondly, they impose the condition that all the system's biases are settled to zero ensuring that there is equilibrium at the zero state in the neurons' dynamics. In

other words, Buckley *et al.* require $y^*=0$ (zero vector), where y^* is a vector describing the position of an equilibrium point in the neuron's state. Consequently they construct a criterion for local stability by linearising the system around y^* looking for the equilibrium point through a Jacobian matrix examination. In brief, their neurocontrollers are locally stable around the zero state if all real parts of the eigenvalues of the Jacobian are negative; otherwise, it is unstable (see also [Strogatz, 1994] for further descriptions of the dynamical systems theory).

In order to obtain bistable neurocontrollers, however, Buckley *et al.* (2008) use *strategy 2* by following experimental descriptions given in [Fine *et al.*, 2007]. The task is phototaxis towards a sequence of lights with a single light sensor. The sensor alternates its position intermittently between the front and back of the agent's body. Since the agent cannot reverse, the nature of the task is fundamentally altered by this unsignalled change to the agent's sensor [Buckley *et al.*, 2008, p. 107]. Therefore, the demand for bistability is methodologically different to the one for monostability. Buckley *et al.* construct a goal-approaching task requiring state and encouraged two modes of behaviour, rather than imposing explicit requirements for bistability at neurocontroller dynamics.

In this chapter, only the *strategy 2* is used to induce mono- and bistability, because it better fits a more traditional ER methodology (see [Buckley *et al.*, 2008, p. 112]). The criterion is to select the conditions that favour the emergence of both types of dynamics rather than imposing dynamical restrictions at neural level. To attain bistability, this work proposes to set differently a and b parameters in Eq. 6.5 and Eq. 6.6: $a=1/3$ and $b=10$ for bistability, while $a=2$ and $b=4$ for monostability. These values are obtained after a trial-and-error process. The question that arises is: why should changing the a and b parameters in Eq. 6.4 lead to mono or bistability in the resulting networks?

By replacing $a=1/3$ in Eq. 6.5, we find that a bistable agent obtains maximum avoiding fitness (i.e. value 100) after moving far away from an avoiding object (i.e. more than 300 arbitrary units). However, in the case of monostable agents (replacing $a=2$ in Eq. 6.5), the maximum fitness for avoiding is reached by moving at least 50 arbitrary units. These values of 'a' parameter implicitly impose that bistable agents must move farthest (6 times more) than monostable agents for maximum fitness. When replacing $b=10$ in Eq. 6.6, the requirement of approaching in bistable agents is that, in the end, maximum fitness can be reached with distances lower than 10 arbitrary units. For monostable agents, and if we replace $b=4$ in Eq. 6.6, such distance can be lower than 25 arbitrary units. These values of 'b' parameter therefore implicitly impose that bistable agents move in the long run closer (0.4 times more) to objects than monostable agents for the approaching task.

The difference between these critical distances for maximum fitness in the bistable case (i.e. approaching: <10 arbitrary units; avoiding: >300 arbitrary units) is considerably greater than in the monostable situation (i.e. avoiding: <25 arbitrary units; approaching: >50 arbitrary units). Note then that the evolutionary requirement of a higher difference in critical distances is what induces the emergence of two dynamical states in the autonomous dynamics (bistable neurocontrollers).

Furthermore, the reduced difference in critical distances induces no further states in the autonomous dynamics of the monostable agent. Proceeding in this way, we obtained 87% bistable and 99% monostable controllers with (a=1/3; b=10) and (a=2; b=4) of 20 independent evolutionary experiments for each type of controller. Appendix A.3 demonstrates that by using the described values of (a; b) parameters for mono- and bistability, the comparison of lifetime-fitness between sets of agents is possible.

It is worth noting that when a network is embedded in an agent body, and despite both kinds of neurocontrollers being driven with time-varying inputs from the sensors, the mono- and bistable distinction has to be made in order to determine the number of basins of attraction used during agents' coupling with the environment. Following the statistical analysis given in [Buckley *et al.*, 2008], work in this chapter tests for mono- and bistability by allowing each network to settle down (10000 time steps) from 1000 different uniformly-distributed random neural activations ($y_i \in [-10, 10]$). This analysis shows that the outputs of networks are globally stable for monostability, or reveals the presence of two fixed-point attractors for bistability. It should be noted that other ways of analysing the emergence of mono- and bistability are also possible using the dynamical systems theory [Strogatz, 1994].

6.3.5 Experimental procedure

The implemented algorithm evolves agents that can accurately distinguish between 'passageways' (approaching objects) and 'obstacles' (avoiding objects). To perceive whether an aperture between objects is 'passable', an agent must discriminate the aperture's width relative to its own body. An agent is placed along the bottom part of a two dimensional environment with no limits. The agent is able to move horizontally with velocity in range [-10, 10] (arbitrary units per time step) to the rightward or leftward direction. The horizontal velocity is proportional to the sum of the opposing output signals produced by two CTRNN motor neurons. Based on Eq. 6.2, the motor output equation controlling the movements of an agent is: *motorLeftOutput – motorRightOutput*.

The agent moves according to first-order dynamics, with motor neurons directly specifying the velocity of movement with a constant of proportionality. This constant is an evolved output-scaling factor for each neurocontroller in range [0, 10]. Objects fall from above with a constant vertical velocity of -3 units per time step (otherwise specified during tests with perturbations). During evolution, objects have a fixed vertical initial distance to the agent's position of 270 units (at zero agent-object distance) with a fixed horizontal offset in range [-100, 100].

Two diamonds each 30 units wide compose both the approaching and avoiding objects. The distance between the centre of these objects represents the objects' horizontal *aperture* forefront, where for approaching the aperture is 90 units (namely, d=3.0, three times the diameter of the agent). For avoiding, the separation is 30 units between the centre of diamonds (d=1.0, once the diameter of the agent), which means no separation between the edges (Figure 6.1).

6.4 Results

Some preliminary settings were tested to evolve a categorical perception task as specified in section 6.3.1. In these experiments, a lower number of sensors were available (2, 4, or 6 sensors), and/or the number of interneurons was reduced from 5 to 4, 3, or 2 neurons. After five independent evolutionary runs for each parameter configuration, the evolution of agents with these numbers of interneurons and sensors did not produce better categorical perception than experiments with 5 interneurons and 7 sensors. For the experimental conditions given in section 6.3, preliminary tests (non-reported experiments) showed that this last combination of neurons and sensors may be the necessary minimum for high performance on simultaneous approaching and avoiding tasks. The sections that follow consequently report results only with mono- and bistable controllers using 7 sensors, 5 fully connected interneurons, and 2 motor neurons.

6.4.1 Statistical analyses of sets of agents

6.4.1.1 Lifetime categorical perception performance

This section contrasts the median lifetime fitness of two different sets of agents: one with 20 monostable agents, and another one having 20 bistable agents. Each agent of both types was obtained as the best-fit individual in the last generation of one independent evolutionary run (section 6.3.3). These two sets are referred to as 'sets of agents to compare' forefront.

Figure 6.2 shows the results obtained on the median lifetime fitness for both sets. Each agent of each type achieves a mean lifetime greater than 90% in tests after evolution. The best agent of each set has a mean fitness (1000 independent experiments) of 91.51% and 97.21% for the mono- and bistable case, respectively. The better median performance of bistable agents (Figure 6.2) is confirmed using a significant *t*-test that supports such positive difference, which is based on a normal distribution assumption, but comparisons of medians are reasonably robust for other distributions.

As we can observe from Figure 6.2, both sets of agents produce proper categorical perception, but the bistable set reaches better median fitness. Box-plots and whisker plots in Figure 6.2 (as well as in all box-plots reported here) have lines at the lower quartile, median, and upper quartile values. Whiskers extend from each end of the box to the adjacent values in the data. These values also include the extreme ones within 1.5 times the interquartile range from the ends of the box. Outliers are data with values beyond the ends of the whiskers displayed with a '+' sign. Notches show the variability of the median between samples.

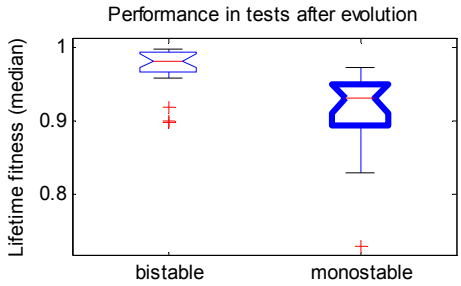
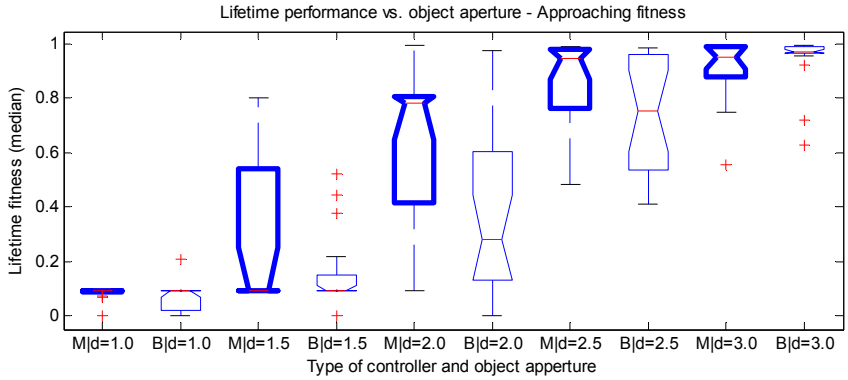


Figure 6.2 – Lifetime fitness (median) for mono- and bistable agents compared in a box plot representation. Fitness is clipped in range [0, 1]. 1000 independent experiments for each agent (20 in total for each type). Networks are composed by 7 sensors, 5 fully-connected interneurons, and 2 motor neurons. The task relates to catching (d=3.0) and avoiding (d=1.0) behaviours where object are dropped from 41 different starting positions in range [-100, 100] (horizontal agent-object relative distance). Results indicate a significant better lifetime fitness by bistable than monostable agents for categorical perception.

The following experiments investigate the capacity of both sets of agents to generalize the perception of objects for approaching and avoiding behaviour. These experiments define separations between diamonds that are not the same as the ones presented during evolution (i.e. d=1.0 and d=3.0 as explained in section 6.3.5). Figure 6.3 shows the median performance (y-axis) of both sets of agents relative to different 'd' apertures between diamonds (x-axis). The obtained median performances for d=1.0 in avoiding (Figure 6.3-B) and d=3.0 in approaching behaviours (Figure 6.3-A) are near the optimum (median) fitness for both types of agents.

For approaching behaviour, a t-test of significance reveals that we cannot reject the null hypothesis that mono- and bistable median fitness are equal for d=1.0, d=1.5 and d=3.0 separations (Figure 6.3-A). However, we can reject the null hypothesis for d=2.0 and d=2.5. This means that the monostable set obtains a good lifetime median fitness when the separation between diamonds enables approaching behaviour (i.e. d=2.0 and d=2.5). For other apertures between diamonds (i.e. d=1.0, d=1.5, and d=3.0), both strategies obtained quantitatively similar performances with a 95% confidence level (5% of significance level) for the true similarity in medians. For avoiding fitness (Figure 6.3-B), we cannot reject the null hypothesis when d=1.0, d=1.5, d=2.5, and d=3.0; however, we can reject it when d=2.0. What these last results indicate is that for d=1.0, d=1.5, d=2.5, and d=3.0, the difference in mono- and bistable performance is not considerably high, which suggests a similar overall performance for both sets of agents in approaching and avoiding tasks.

[A]



[B]

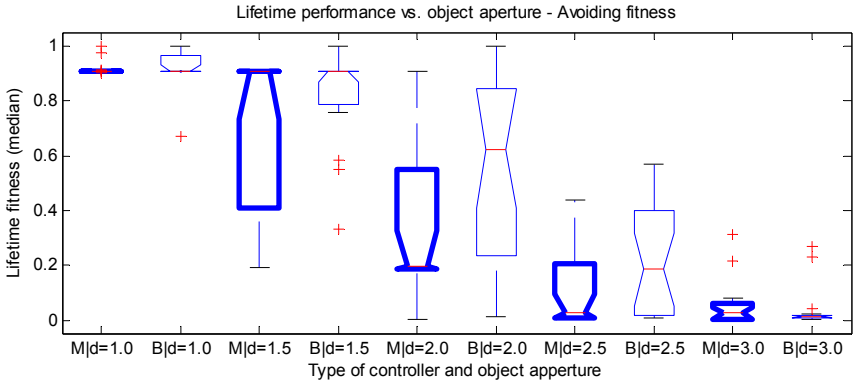


Figure 6.3 – Lifetime fitness (median) of (M) mono- and (B) bistable agents (20 for each type) with a box plot representation for various object apertures (d=1.0, d=1.5, d=2.0, d=2.5, and d=3.0). Fitness is clipped in range [0, 1]. Fitness measures are divided into [A] approaching and [B] avoiding measures. Objects are dropped from agent-object distances in range [-100, 100]. Plots indicate that monostable controllers obtained better lifetime median fitness than bistable agents when the separation between diamonds are d=2.0 and d=2.5, and these separations were not the same than the ones presented during evolution, namely d=1.0 and d=3.0.

Summarizing, both mono- and bistable agents perform a sharply approaching behaviour when d=3.0, and avoiding behaviour when d=1.0. For intermediate separations between diamonds like d=2.0 and d=2.5, monostable agents show better approaching than bistable ones (higher median fitness in Figure 6.3-A); while bistable agents perform better than monostable agents for avoiding (Figure 6.3-B). It is worth noting here that bistable agents generally received less score in comparison to monostable ones not because they equivocated between approaching and avoiding movements, but because they ended up colliding with the middle of one of the diamonds.

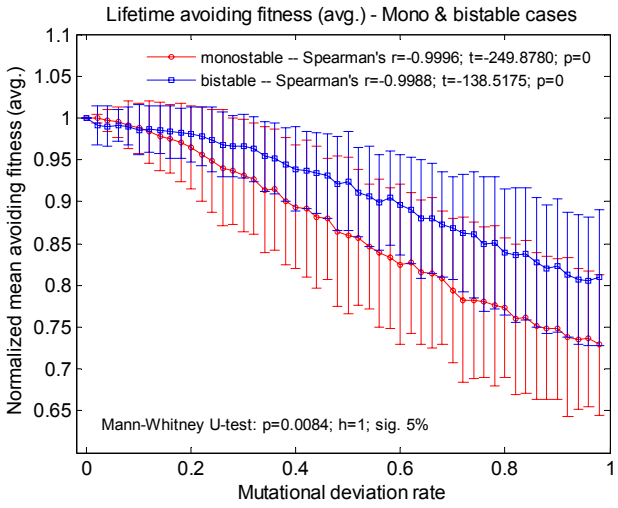
6.4.1.2 Performance with mutational perturbations

Results here and in sections 6.4.1.3 and 6.4.1.4 give evidence whether mono- and bistable sets share similar capacities to sustain behaviours in the presence of 'extreme perturbations'. The concept of extreme perturbations refers to mean situations that negatively affect the production of behaviours, where these situations were not given during the evolution of agents.

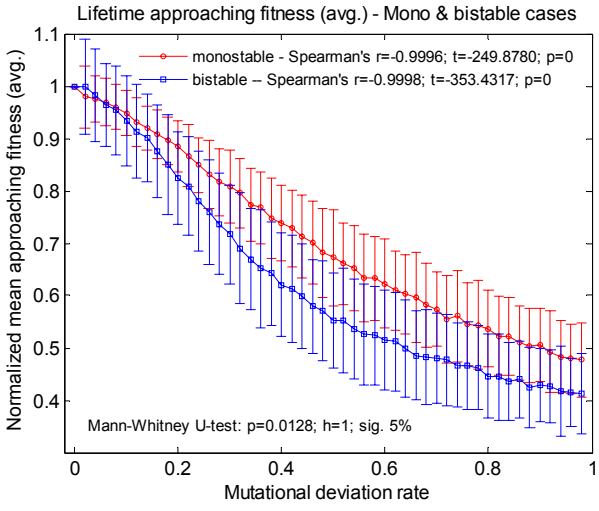
Figure 6.4 shows the normalized lifetime (mean) fitness of the set of mono- and bistable agents discriminated by different levels of mutational perturbations and avoiding/approaching fitness. Perturbations are applied to agent genotypes as mutations to each gene and, after translating them to their phenotypic expressions, the algorithm measures agent fitness. The algorithm repeats this process 1000 times for each agent taking the mean fitness, and averages the performance (*y*-axis) of the whole set of agents for each level of perturbation (Figure 6.4). Random mutations to genes (in range [0.0, 1.0]) are normally distributed with zero mean and controlled deviation (*x*-axes in plots of Figure 6.4). Values lower than 0.6 of mean (normalized) fitness in Figure 6.4 indicate that agents cannot produce approaching or avoiding behaviours.

Both types of agents usually produce proper avoiding behaviour despite perturbations, because the mean fitness in Figure 6.4-A is higher than 0.7 (*y*-axis). Results indicate a small but significant higher mean fitness by the monostable set across levels of mutational perturbations in sustaining approaching behaviour (Figure 6.4-B). For avoiding behaviour (Figure 6.4-A), the mean fitness indicate a better performance for the bistable set of agents at most levels of mutational perturbation. The Mann-Whitney U-test [Mann & Whitney, 1947] for each plot supports the validity of these differences with 5% of significance. Plots in Figure 6.4 include metrics of significance based on the Spearman's rank (*s*) coefficient, the associated *t*-test (*t*) and p-values (*p*) showing the correlation between the mutation deviation rate (*x*-axis) and the normalized mean fitness value (*y*-axis). These tests of significance indicate that such a correlation is slightly higher for the mono- than for the bistable set in avoiding behaviour (Figure 6.4-A), but lower for approaching behaviour (Figure 6.4-B). In other words, the higher the induced mutation deviation is, the lower mean avoiding fitness the monostable set reaches, where such decay of the mean fitness is less evident for the bistable case (Figure 6.4-A). Finally, for bistable agents, the higher the mutation rate is, the lower mean approaching fitness they reach, where this decay is more evident than in the monostable set (Figure 6.4-B).

Summarizing, results indicate that there is a slight but significant tendency toward more a robust approaching performance by monostable agents than bistable ones based on analysis with mutational perturbations (Figure 6.4-B). This tendency appears mainly because bistable agents move farther than monostable agents in the presence of these perturbations in the approaching task (Figure 6.5-B), where the former agents are rewarded with lower approaching fitness. Monostable agents however cannot obtain higher mean fitness in avoiding than bistable agents under mutational perturbations (Figure 6.4-A). This is also because bistable agents can move farther than monostable agents in the presence of these perturbations, and consequently the former agents obtain better avoiding fitness (see explanations on the fitness function given in section 6.3.3).

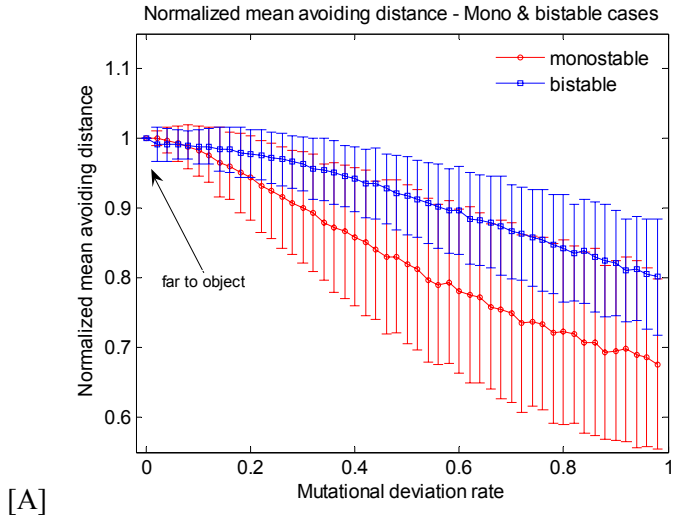


[A]

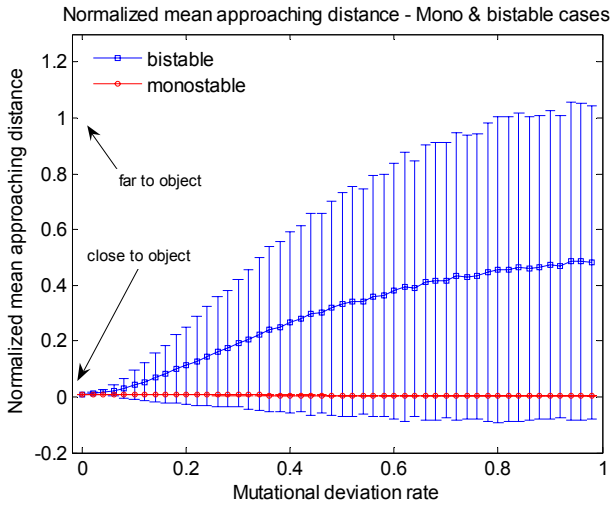


[B]

Figure 6.4 – Normalized lifetime (mean) fitness based on mono- and bistable sets of agents in the presence of mutational perturbations. Twenty (20) agents compose each set. Each data point represents the mean fitness of 1000 independent experiments. Perturbations are applied to agent's genotypes and after translating them to their phenotypic expressions, we take agent's normalized performances (*y*-axis). Mutations to genes are normally distributed with zero mean and controlled deviation in range [0, 1] (*x*-axis). Error bars represent standard deviation. Plots stand for mono- and bistable agent's performances based on [A] avoiding and [B] approaching fitness. Results indicate a small, but significant difference in favour of the monostable set in sustaining approaching behaviour ([B]) despite induced mutations. For avoiding behaviour ([A]), the mean fitness trajectories indicate an overall better performance for the bistable set. Differences in mean fitness are supported by a Mann-Whitney U-test of significance (see imprints in each plot).



[A]



[B]

Figure 6.5 – Normalized (mean) agent-object distance for tests after evolution (lifetime experiments) based on mono- and bistable sets composed by 20 agents each. Each data point represents mean distance over 1000 independent experiments. Results are shown for mono- and bistable agents at different induced mutational deviations (*x*-axis) in agent's genotypes. After mutations, we translate the resulted genotype to their phenotypic expression, evaluating the agent's performance in order to obtain the final relative agent-object mean distance (*y*-axis). Mutations are normally distributed with zero mean and controlled deviation in range [0, 1] (*x*-axis). Error bars represent standard deviation. Plots correspond to mono- and bistable agent's performances based on agent-object distances after [A] avoiding and [B] approaching behaviours. Results on [B] plot indicate that monostable agents remain closer to approaching objects in comparison to bistable ones in the presence of mutational perturbations. The [A] plot indicates that bistable agents move farthest than monostable agents in avoiding behaviour in the presence of mutational perturbations.

6.4.1.3 Performance with changing-object perturbation

Continuing the discussions of the statistical tendency of both sets under perturbations, this section shows analyses of the capacity of both sets of agents to recognize changes in aperture between dynamics while objects fall.

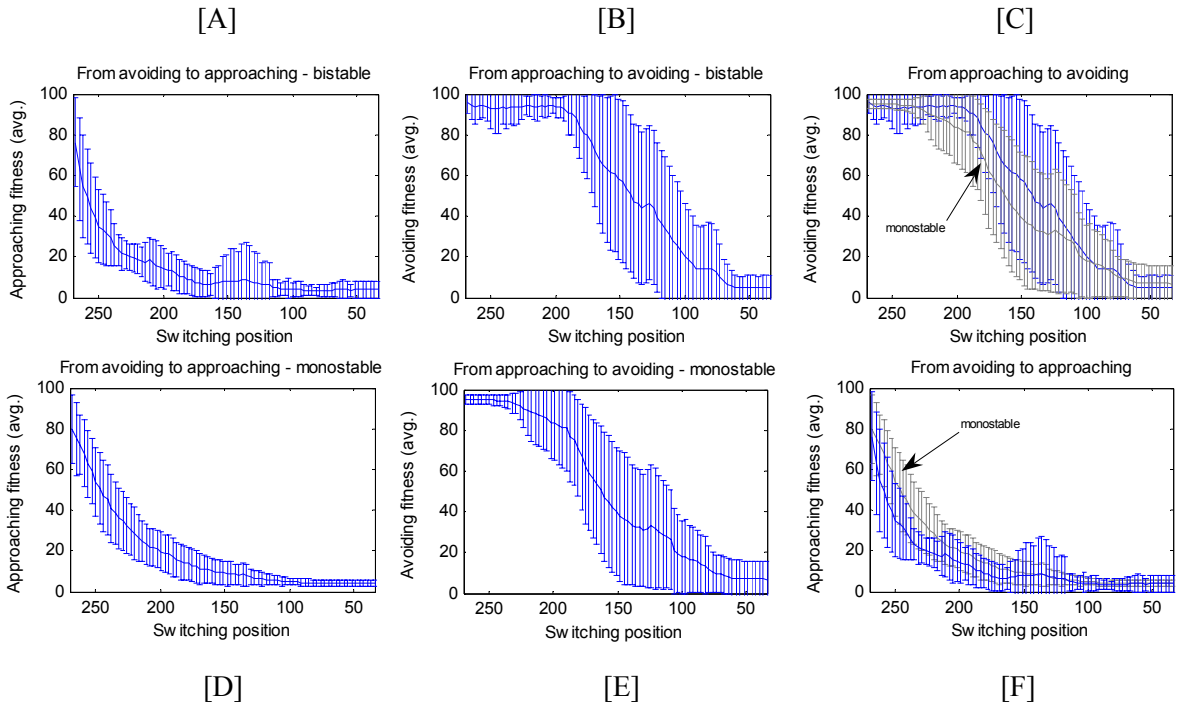


Figure 6.6 – Performance (avg. of mean fitness) of mono- and bistable set of agents after changing from avoiding/approaching to approaching/avoiding falling objects at different vertical positions (*x*-axis). Objects fell down from 41 different horizontal agent-object positions in range [-60, 60]. The object's switching position over time is plotted for an aperture relative to agent body's size for [A & D] approaching (d=3.0) and [B & E] avoiding behaviour (d=1.0). [C & F] show an overlapped representation of first and second columns for each row. Error bars indicate standard deviation. Plots show similarity in mono- and bistable agent's capacity to produce behavioural changes according to the falling object.

Figure 6.6 shows the performance obtained (avg. of mean fitness) in approaching (d=3.0) and avoiding (d=1.0) tasks when the type of falling object is changed at different vertical positions (e.g. from avoiding/approaching to approaching/avoiding). Note first that the dissimilarity between curves in Figure 6.6-C & F is not statistically significant, but indicative of the sort of categorical behaviour employed by both sets of agents. For certain changing positions, the fitness of the monostable set does show less variability from their means (standard deviation) in comparison to the one for bistable agents. This lower variability mainly appears from 275 to 230 units switching positions (*x*-axis) for approaching-to-avoiding objects (Figure 6.6-B & E). Bistable and monostable agents obtain a nearly constant low performance at the latter switching

positions for avoiding-to-approaching tasks. This is shown in Figure 6.6-A & D from 170 to 36 switching positions. One explanation for this low performance is that mono- and bistable sets did not react as fast as required after the change of object, losing contact as the object fell, due to initial avoiding movements.

Figure 6.6-A & D also suggest that the reaction of mono- and bistable agents to changes in object does not show a considerably high mean fitness in avoiding to approaching, mainly between 270 to 250 switching points. Finally, it should be noted that in approaching-to-avoiding tests, bistable agents (Figure 6.6-B) show less variability (standard deviation from the mean performance) than the monostable set agents (Figure 6.6-E) from 240 to 180 switching steps. This is because agents in the former set go farther more frequently from the new avoiding object in comparison to agents in the latter set after sensing an avoiding object.

According to Figure 6.6, the overall observation is that for both types of agents the capacity to discriminate objects shows dependence on the agent position, the horizontal object starting position, and the vertical relative-distance between the agent and the object (approaching or avoiding ones). This suggests that some aspects of the agents' situated state corresponds with the layout of both diamonds at the early trial midpoint when the object begins its fall.

6.4.1.4 Performance with environmental and neurocontroller perturbations

The motivation behind the following analysis is to understand the effects of environmental and neurocontroller perturbations on lifetime (mean) fitness during categorical perception. Here the algorithm induces different levels of additive and multiplicative noise in incoming or internal signals, as opposed to the mutational change indicated in section 6.4.1.2.

Figure 6.7 shows results from experiments testing the performance of the mono- and bistable sets of agents discriminated by degrees of perturbation, i.e. 20%, 40%, 60%, 80%, 100%, and 120% at *x*-axes. Percentages apply to perturbations affecting sensory, neural or motor signals that agents should process. For each signal, the algorithm adds a uniformly distributed, randomly selected value that is multiplied by these percentages. Plots in Figure 6.7 are also divided into:

(a) environmental perturbations at object level: (*a.1*) noise in the velocity of falling objects, and (*a.2*) noise in the separation between diamonds;

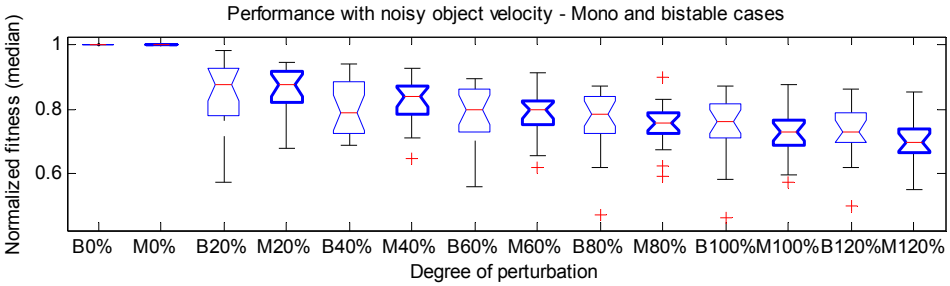
(b) additive perturbations at signal level: (*b.1*) noise in sensory incoming signals, and (*b.2*) noise in the activity of neurons;

(c) multiplicative perturbations at neurocontroller level: (*c.1*) noise in synaptic connections, and (*c.2*) noise in neuron gains.

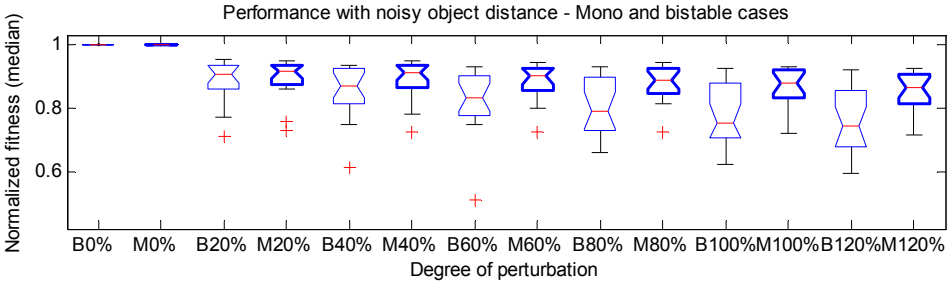
Perturbations *a.1*, *a.2* and *b.1* have some relation between them because they refer to 'environmental perturbations' as well, while *b.2*, *c.1*, and *c.2* relates to 'perturbations affecting the neurocontroller'. For all of these perturbations, the algorithm implements a pseudorandom (uniformly distributed) additive noise to signals in a range [0.0, 1.0] proportionate to the degree of

perturbation. The following results are reported for 200 independent experiments per agent in each set discriminated by the level of perturbation (Figure 6.7).

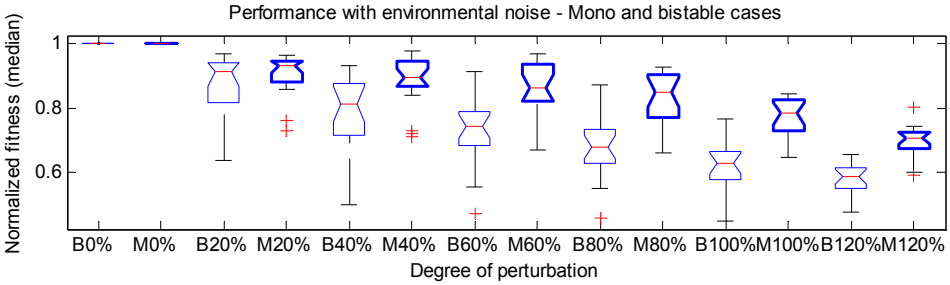
[a.1]



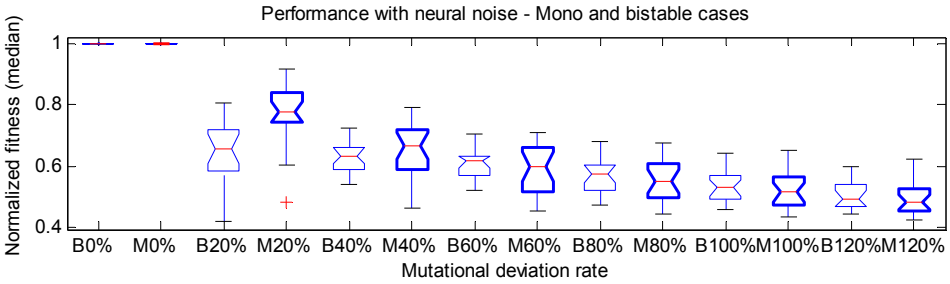
[a.2]



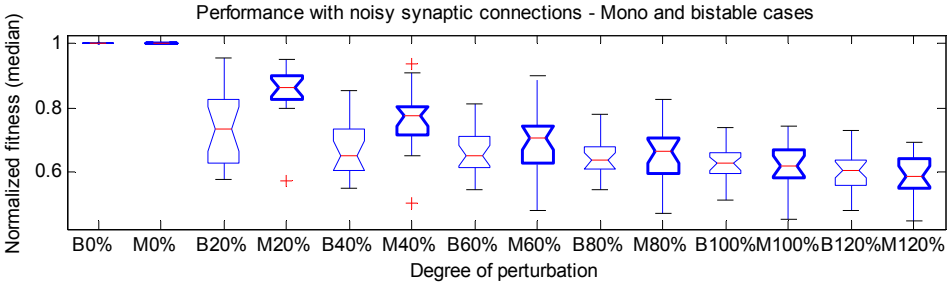
[b.1]



[b.2]



[c.1]



[c.2]

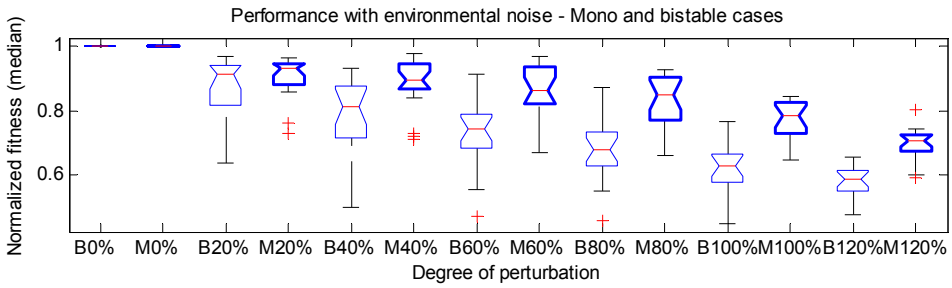


Figure 6.7 – Lifetime fitness (median) obtained for mono (*M*)- and bistable (*B*) sets at different degrees of perturbations (*y*-axis). Each data point represents 200 different experiments for each agent (20 agents per set). Perturbations are divided as: (*a*) environmental perturbations at perceived object level: (*a.1*) noise in the velocity of falling objects, and (*a.2*) noise in the separation between diamonds; (*b*) additive perturbations at signal level: (*b.1*) noise in incoming sensory signals, and (*b.2*) noise in the activity of neurons; (*c*) multiplicative perturbations at neurocontroller level: (c.1) noise in synaptic connections, and (*c.2*) noise in neuron gains. Plots indicate a slight, but significant overall tendency to better performance by monostable agents in most of perturbation tests (see the main text for further descriptions). Results also indicate similar median performances in *a.1*, *b.2*, and *c.1* experiments.

Figure 6.7 shows that mono- and bistable sets obtain a similar median fitness for most degrees of perturbation in tests with noise in the velocity of falling objects (*a.1*), noise in the activity of neurons (*b.2*), and noise in synaptic connections (*c.1*). A significant difference in median performances in favour of monostable agents is observed when we induce noise in incoming signals (*b.1*), and noise in the separation between diamonds (*a.2*). For *a.2* and *b.1*, there is a lower decay of the median performance for the monostable set in comparison to the bistable case. The lower decay is evidenced after inducing noise in incoming signals (*b.1*), noise in the activity of neurons (*b.2*), and noise in synaptic connections (*c.1*) for certain levels of perturbations (see Figure 6.7). In these observations, we account for fitness differences with 95% confidence (5% of significance level); i.e. median fitness for mono- and bistable set of agents differ when the notches do not overlap for each pair of test (e.g. B20% and M20% in *x*-axis of Figure 6.7-*b.2*).

Results in this section indicate a higher median fitness tendency by the monostable set of agents than the bistable ones after inducing some levels of sensory perturbations (e.g. results with noise in incoming signals, and noise in the separation between diamonds in Figure 6.7). We cannot observe, however, an overall significant difference in fitness from the rest of the perturbations. The next section provides behavioural analyses with the two randomly selected agents, one of each type. This is done in order to exemplify what produces such a positive tendency to better median fitness in monostable agents.

6.4.2 Behavioural analyses of selected agents

Before describing the indicated behavioural analyses, this section briefly exemplifies the output responses of a mono- and bistable controller after allowing each network to settle down (10000 time steps) from 1000 different random neural activations ($y_i \in [-10, 10]$) (Figure 6.9). These two agents are representative examples of the mono- and bistable sets of agents. The remaining

sections of this chapter also report results for these two (randomly selected) agents. Appendix A.2 describes the structure of the agents' neurocontrollers in detail.

Figure 6.8 shows the number of activated sensors for both behaviours when objects are placed at different agent-object separations in the arena. Regions in which the agent is fully sensing the object (e.g. the central region in the avoiding case, Figure 6.8-B) are bright meaning that all sensors are activated, whereas those with fewer activations are darker. Plots in Figure 6.8 show the full range of sensory activations that agents encounter.

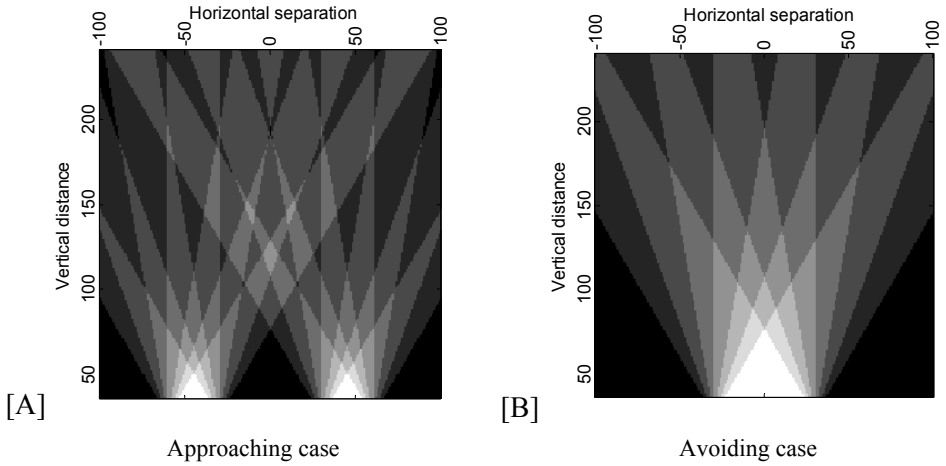


Figure 6.8 – Sensor activation for approaching [A] and avoiding [B] behaviours. Dropped objects have two diamonds of diameter 30 placed at different starting horizontal (range [-100, 100]) and vertical (range [35, 265]) positions. The object's aperture is d=1.0 and d=3.0 for avoiding and approaching objects, respectively. Plots represent the number of activated sensors that an agent would eventually process if an object were fixed at that location in its field of view at each point as a function of x-axis and y-axis. The intensity of the grey shade regions represents the number of activated sensor ranging from bright (all sensors activated) to dark (no sensors activated).

Our tests show that monostable controllers were globally stable in their autonomous dynamics based on one steady state in output responses (see Figure 6.9-B caption). Again, we distinguish mono- and bistable controllers based on the number of steady states exhibited by the autonomous responses of mono- and bistable controllers (i.e. when inputs are 0000000). Bistable controllers, however, presented globally stable network output derived two fixed-points within the intrinsic dynamics of controllers. Only to check that mono- and bistable agents show one or two stable points, respectively, for any combination of incoming signals, we fixed the incoming signal of their 7 sensors to a specific sensory pattern (each binary representation in y-axis in Figure 6.9). The number of points differentiates derived from the given sensory pattern. For example, the bistable controller showed two stable point near ±0.5 and 0 but it is so only for some sensory patterns (e.g. 0000000); while for other patterns it presented only one point overtime (e.g. 0-output value for 1111111 in Figure 6.9-A). Note that the number of steady states (two or one) in the bistable case cannot be deduced for each sensory pattern before testing the output response of

controllers. An explanation of this difficulty rises in that both approaching and avoiding behaviours are simultaneously 'coded' in neurocontrollers by the evolutionary process. This also holds for the monostable agent.

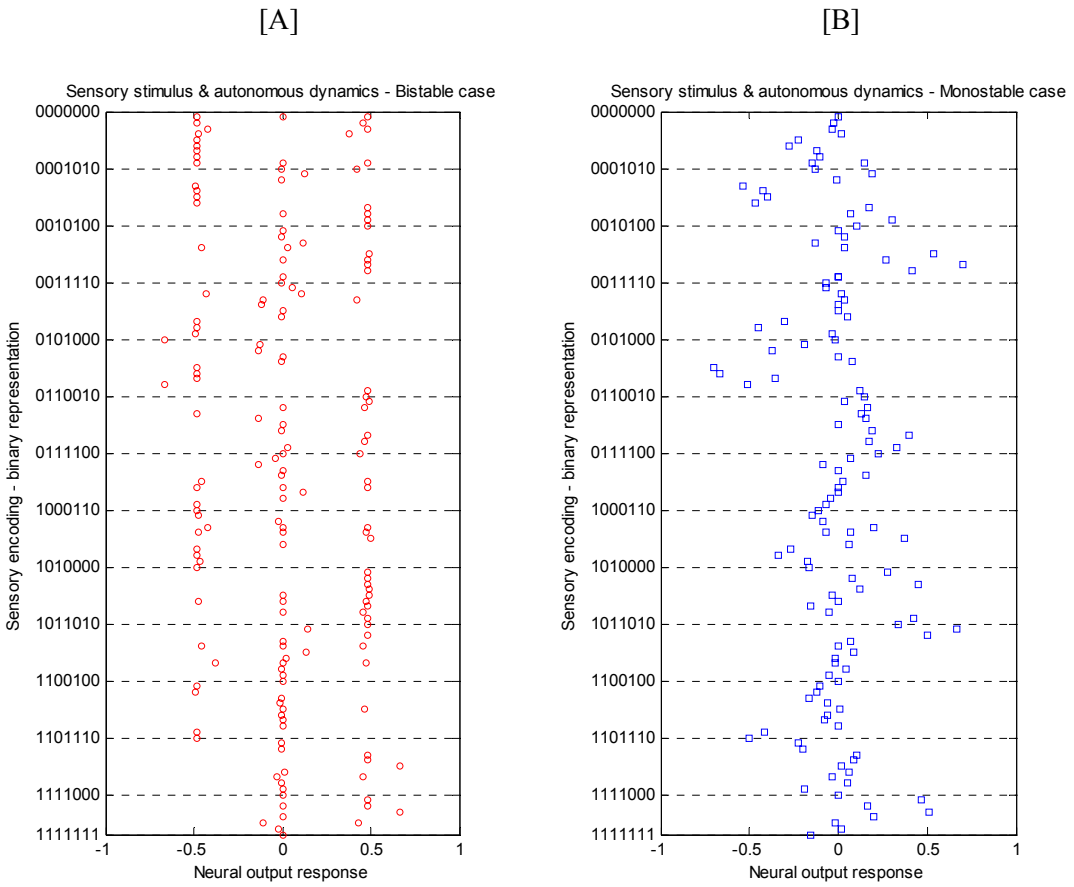


Figure 6.9 – Example of output responses (difference between motor neuron outputs) for a bistable (circles) and monostable (squares) neurocontrollers. Output responses differentiate according to a given sensory incoming after the network settle down (10000 time steps) from a random set of neural activations. The sensory incoming is represented as a binary array of 7 binary values in *y*-axis. For each label in *y*-axes, 1/0 represents the on/off state of sensors. Graphics show that [A] the bistable controller produce outputs around ±0.5 and/or 0 values in *x*-axis depending on the given sensory pattern (*y*-axis). Because the imposed model symmetry, this represents two stable states of the long-term dynamics of agents (e.g. 0000000 representing the absence of sensory stimuli). In the monostable case, [B] the network shows only one response for each sensory incoming at *y*-axis over the range [-0.7, 0.7].

As an example of such difficulty, note that a small change in sensory incomings, e.g. 0000001 and 0000010, differently generate slight leftward movements (*x*-axis negative differences) for the monostable agent in Figure 6.9-B. The 0000011 sensory pattern however generates a rightward movement (*x*-axis positive differences) at long run (Figure 6.9-B). Some sensory patterns like 1111111 produces a slight movement to the leftward side, but the deactivation of sensor 7

(1111110 pattern) generates a change of direction to the rightward side; while the non-evident effect of deactivation/activation of sensors, e.g. 1111101 and 1111100, generates a movement to leftward and rightward sides for the monostable agent, respectively. These examples show that the correspondence of a sensory pattern and the dynamics of the agent over the long term can be quite complex to generalize and nonlinear.

6.4.2.1 Approaching and avoiding behaviours for discrimination task

This section investigates how a randomly selected agent from each set produces behaviours when the aperture between diamonds are the same as the ones for which agents evolved (i.e. d=1.0 for avoiding and d=3.0 for approaching). Analyses here look for behavioural explanations as to when approaching and avoiding behaviours initiate, based on object aperture detection.

Plots in Figure 6.10 in E & G show the trajectories in the arena that one randomly selected monostable agent produces during categorical perception with d=1.0 (avoiding) and d=3.0 (approaching), the separation of the diamonds. Similarly, plots in Figure 6.10-A & C show the corresponding trajectories but for a randomly selected bistable agent. The differently shaded regions of plots in Figure 6.10-*right* represent the long-term horizontal velocity that these agents would finally take if an object were fixed at every location in their vision field. Axes in Figure 6.10-*right* indicate the relative horizontal (x-axis) and vertical (y-axis) agent-object separations. The symmetry of velocities is evidenced by the intensities of the shaded regions, ranging from dark (no velocity) to light grey (high velocity). For instance, the long-term approaching velocity in the bistable case (Figure 6.10-B) shows dark regions representing no movements of the agent mainly when the agent centres the object. Light grey regions stand for fast rightward or leftward movements for approaching behaviour.

An interpretation of the long-term velocities related to sensory activation is difficult to examine without the appropriate agent-object horizontal position. However, Figure 6.10 suggests that part of the monostable agent's strategy in approaching and avoiding tasks grounds on tracking the object during its fall. Figure 6.10-E & G shows that the monostable agent produces nearly straight trajectories in the boundary of the arena from 40 to 80 elapsed times, mainly in the avoiding situation. This behavioural strategy is not observed in the analysed bistable agent (A & C plots), where this agent can move rightward or leftward without maintaining contact with a falling object.

By further analysing the behaviour of both selected agents, and plotting the evolution of the horizontal separation between each of them and the centre of the object's aperture (Figure 6.10-A, C, E & G), we can see that both agents make a clear categorical distinction between approaching and avoiding objects. This difference mainly appears when the horizontal separation between the agent and the object is in the range [-60, 60]. Consequently, the rest of this work focuses on behavioural descriptions in such horizontal range.

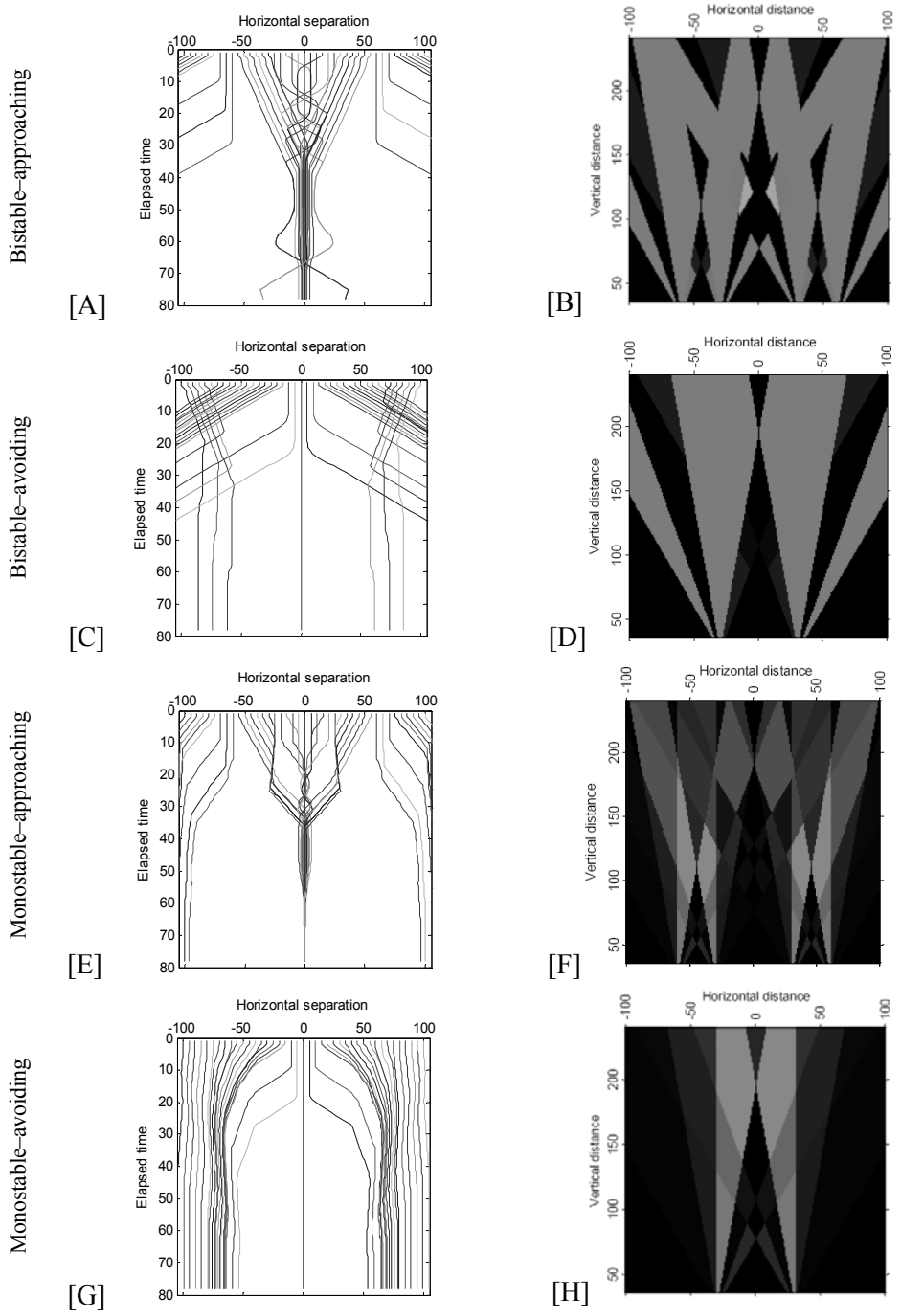
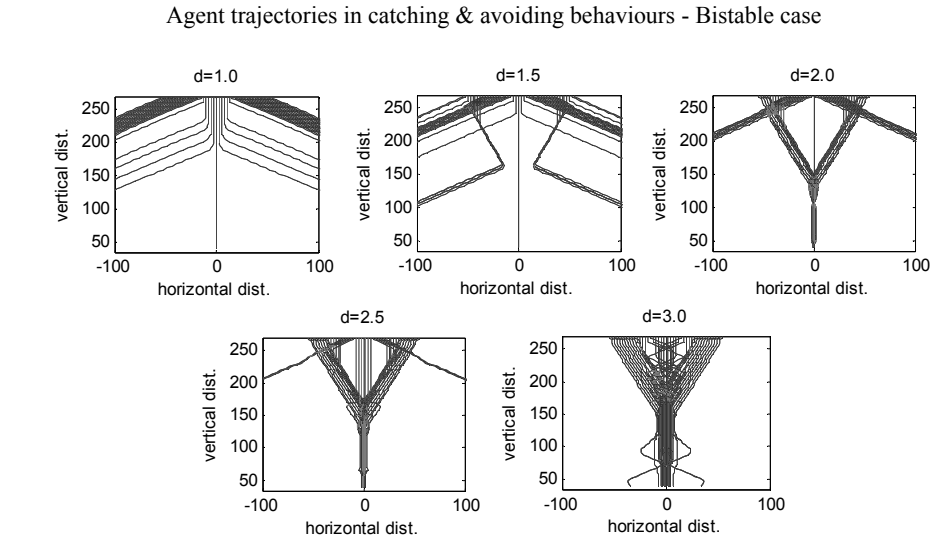
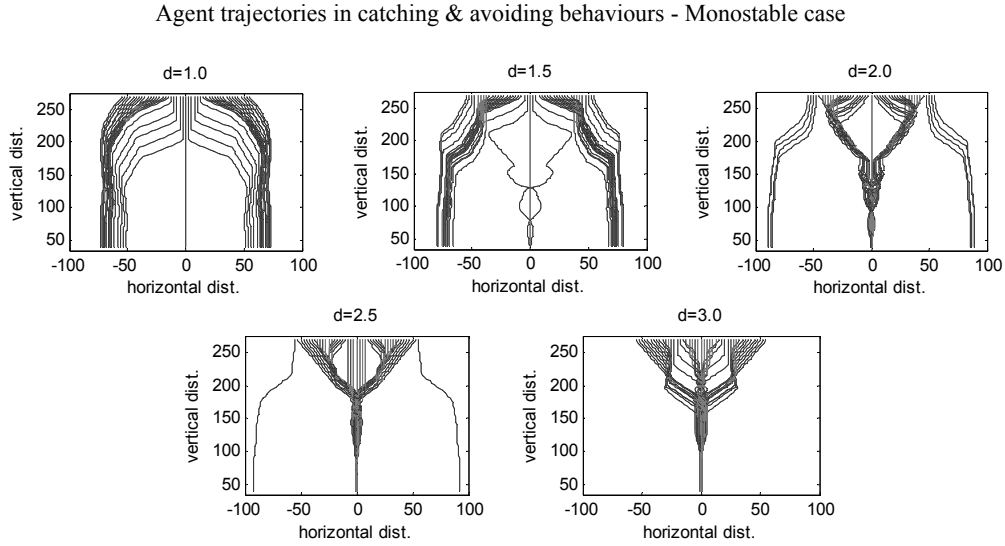


Figure 6.10 – Example of the trajectories in the arena (*left column*) and the steady-state horizontal-velocity field (*right column*). Plots are divided into behaviours for mono- and bistable agents in approaching and avoiding tasks (see labels in each plot). The *right column* shows different shaded regions for the long-term horizontal velocity that the agent would eventually adopt if an object were fixed at that location in its field of view. Trajectories suggest that part of the monostable agent's strategy for solving the approaching and avoiding behaviours is based on 'tracking the object' during its fall, which is evidenced as a relatively constant horizontal separation throughout most of elapsed time (*y*-axis in [E] and [G] plots). This continuous tracking is not mostly observed for the bistable agent in [A] and [C] plots. Right column plots are obtained by scaling velocities in [0, 255] range of colour (the relative maximum and minimum velocity representations in each plot).



[A]



[B]

Figure 6.11 – Example of the behaviour of a [A] bistable and [B] monostable agent in approaching and avoiding tasks. Objects are dropped from different agent and object horizontal distance in range [-60, 60] (*x*-axis). The object horizontal and vertical positions are plotted over time for *d*=1.0, *d*=1.5, *d*=2.0, *d*=2.5, and *d*=3.0 apertures (relative to agent body's size). Trials begin at top and time increases from top to bottom in each plot. Plots indicate clear strategies for categorical perception in relation to apertures between diamonds given during evolution (*d*=1.0, *d*=3.0). See main text for further descriptions.

Depending on the initial horizontal offset of the object, the trajectories of both selected agents (Figure 6.10) can be grouped into two distinct bundles, namely fast approaching/avoiding or scanning movements. Figure 6.11 gives examples of this distinction with *d*=1.0 and *d*=3.0 apertures (see caption). Mostly when the object intersects one of the farthest sensory rays shortly after a trial begins, it defines avoiding movements for the analysed monostable and bistable agents (e.g. 265 to 250 units of vertical separation in Figure 6.11). Trials that are more central result

predominantly in scanning movements, generating series of actions crossing the midline in each plot. Trials that are more peripheral with approaching objects result in slower centring movements that cross the plot midline fewer times. This scanning behaviour is more frequent for the monostable case than for the bistable agent, increasing when d=3.0 (approaching object) (Figure 6.11). However, scanning is not observed with d=1.0 for both agents. The next section continues investigating what produces switching behaviour in both agents, focussing further on apertures between diamonds different than d=1.0 and d=3.0.

6.4.2.2 Environmentally modulated behavioural switches

After the behavioural analyses given in the previous section, two features of agents' dynamics are assumed to be necessary for the implemented categorical perception task: (*a*) the *initiation* of catching and avoiding behaviours, and (*b*) the capacity of agents to *recognize* objects based on the aperture between diamonds. With the purpose of understanding when avoiding and approaching are initiated in both randomly selected agents, we must examine when behavioural switches appear after changes in perception. This section gives explanations on this point rooted in behavioural analyses of the selected two agents (section 6.4.2.1), and with apertures between diamonds not given during the evolution of agents.

Figure 6.12 shows the behavioural trajectory depicted in the arena by the two previously described agents when the separation between diamonds is d=1.65. Plots B & E in Figure 6.12 (based on Figure 6.12-A & D plots, in that order) clearly show the mono- and bistable agents' attempt to switch behaviours at the trial midpoint (around 150 vertical distance). These switches are the result of the 'uncertainty' of both agents about performing approaching or avoiding behaviours because d=1.65 is a non-evolutionarily presented aperture between diamonds. Furthermore, for d=1.5, d=2.0, and d=2.5 apertures in Figure 6.11, we can also have a bigger picture of when these behavioural switches appear in both agents.

We can hypothesize then that certain state variables (e.g. the agent's place in the arena and its current dynamical state) enable both agents to switch behaviours, rather than being the consequence of an 'internal process' for producing behaviours. In other words, where certain sensory patterns appear, these patterns initiate the approaching or avoiding movements in the analysed mono- and bistable agents. This section further researches on B & E plots in Figure 6.12 to develop a global description of neural activities and their relation to the depicted behavioural strategies.

At the neural level of the bistable agent, the output of the right motor neuron (*mr*) generating the trajectory shown in Figure 6.12-B (B1), starts to decrease after sensor 3 activates (before time step t=35). The agent-object's relative distance produces the sensory pattern 0111000 (the state of each binary sensor) that stimulates the left sensory side of the bistable agent, which creates a leftward movement (negative velocity). This type of sensory pattern mainly affects the activity of an interneuron (neuron 8 forefront), causing a change from maximum (around 1) to minimum

(near to 0) activation. This produces an alteration of the motor neuron *mr* evidenced in the agent's behaviour as shown in Figure 6.12-B (B1) for a vertical separation of 125 units.

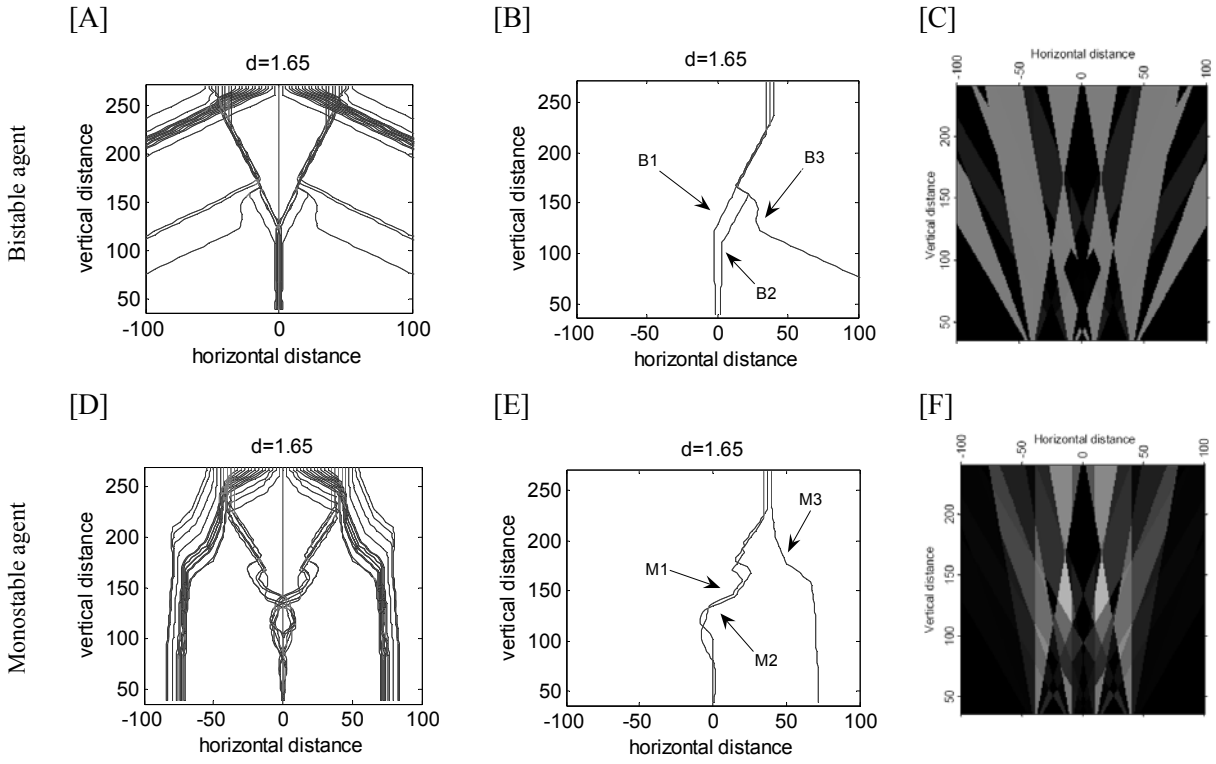


Figure 6.12 – Example of mono- and bistable agent behaviours when objects are dropped from different horizontal positions in range [-60, 60] (*x*-axis). The agent-object horizontal and vertical positions are plotted over time for an aperture of *d*=1.65 relative to agent body's size. Trials begin at the top part of plots and time increases from top to bottom in each plot. From *left* to *right* columns, graphics show the trajectory of agents, the selected trajectories for comparing behavioural switches, and the steady-state horizontal-velocity field, respectively. B_i and M_i labels indicate different trajectories for mono (*M*) and bistable (*B*) agents. Behavioural analyses indicate the 'uncertainty' of agents for performing approaching or avoiding behaviours around 150 vertical distance (*y*-axis).

Interestingly, only the activation of sensor 5 produces an abrupt increase of neuron 8's activity with a direct effect on motor neuron right (*mr*) where the activity of this motor neuron increases over the activity of motor neuron left (*ml*). This effect produces a rightward movement of the agent as shown in Figure 6.12-B (B2). Furthermore, the stimuli represented by the 0111000 sensory pattern, followed by the deactivation of sensor 5, produces a decay and thereafter a maintained low activity of neuron 8 in the B3 agent's trajectory (Figure 6.12-B (B3)). The persistence of this sensory pattern (0111000) creates a constant rightward movement of the agent mainly because of the relative low activity of motor neuron *mr* in comparison to motor neuron *ml*. That is, when the incoming sensory pattern changes from 0111000 to 0111100, the bistable agent avoids the object. The bistable agent then remains moving rightward sustaining the avoiding behaviour. This rightward movement persists after the agent loses contact with the object in the

presence of the 0000000 sensory pattern. Comparing the trajectories in Figure 6.12-B to the ones in Figure 6.12-E, we note that a right- or leftward avoiding movement of the monostable agent cannot persists after the agent loses contact with the object, i.e. approximately 150 units of vertical distance for objects placed around 60 units of horizontal distance (see trajectory M3 in Figure 6.12-E). This observation suggests that the analysed bistable agent can 'remember' a previous movement for avoiding behaviour to one side independently of current perception, which does not hold for the analysed monostable agent. This last point is the focus of discussion in the next section.

6.4.3 Dynamical analyses of selected agents

6.4.3.1 State-dependent dynamics during coupling

This section continues with analyses of the same two randomly selected agents, but concentrating on agent-environment coupled dynamics underlying approaching or avoiding movements after sensing objects.

Plots in Figure 6.13 and Figure 6.14 illustrate the changes in motor dynamics (first columns) for the bistable and monostable agents as a function of the type of object and the agent-object distance (second columns). More specifically, Figure 6.13-A & C and Figure 6.14-A & C show for the bi- and monostable agents the dynamical relation between the left (*ml*) and right (*mr*) motor neuron states (y_i) during approaching and avoiding behaviours (see captions). Figure 6.13-B & D and Figure 6.14-B & D represent the dynamical relation between agent's motor response at *y*-axis (i.e. the difference between motor neurons outputs) and the agent-object relative distance (*x*-axis) for each agent.

Plots in Figure 6.13-B and Figure 6.14-B indicate that these agents finish at distance zero to the object after approaching behaviour (*x*-axis). In the presence of an avoiding object, the bistable agent moves with leftward or rightward direction ($x=\pm 400$ in Figure 6.13-D), while the monostable agent finishes at around 70 units of distance and stops when the object is not sensed (approximate at $x=\pm 70$ in Figure 6.14-D). Plots in Figure 6.14 show that the behavioural strategy in approaching (Figure 6.14-A & B) and avoiding (Figure 6.14-C & D) tasks employed by the analysed monostable agent is rooted in returning to its dynamical state, namely a unique fixed-point attractor. At state space level, this return occurs when the difference in motor neuron activity is zero (dotted straight line in plots of Figure 6.13 and Figure 6.14). Interestingly in Figure 6.13-B, we can see that the presence of an approaching object creates a unique attractor (fixed-point) in the bistable-agent internal dynamics. In this situation, the bistable agent uses a similar strategy to the monostable one to move toward the centre of the diamonds, showing internal transient dynamics around such a state (Figure 6.13-A & B). The presence of an avoiding object, in contrast, does not induce monostability; in fact, it promotes bistability in the agent's neurocontroller (see ± 2.66 and 0 points in *y*-axis of Figure 6.13-D). The bistable agent moves in

the long run to different horizontal directions after sensing a leftward (-20 and -40 object positions) or rightward (20 and 40 object positions) placed avoiding object. Note that the oscillatory behaviour of the bistable agent shown in Figure 6.13-B is not because dynamics actually get to a periodic attractor, but because the system is going through a dynamical bifurcation depending on sensory input (see also Figure 6.9).

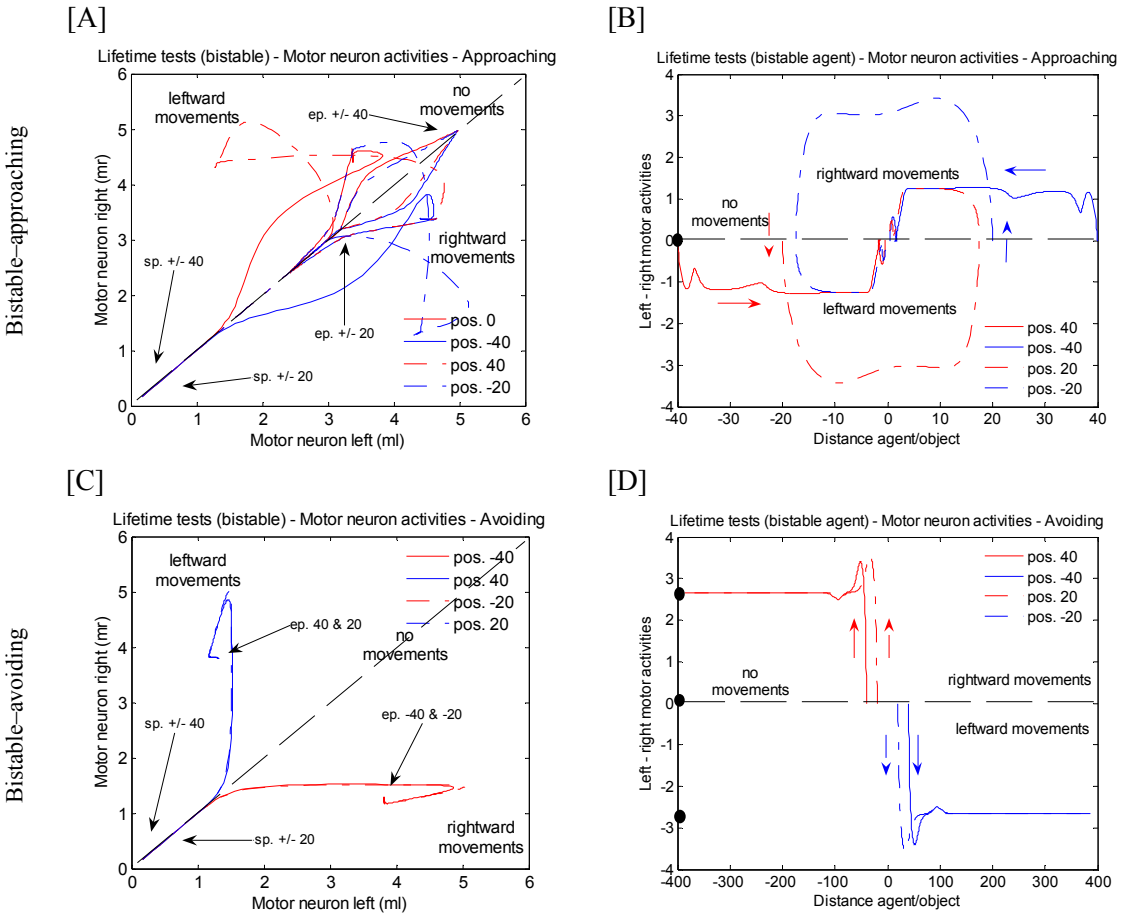


Figure 6.13 - Example of dynamical trajectories when a bistable agent is placed in the environment. Dynamical trajectories [A & C] are plotted for the motor neuron states (y_j) of a bistable agent; [B & D] indicate the dynamical relation between the difference of left (*ml*) and right (*mr*) motor neuron states (y_i) during approaching and avoiding behaviours, and agent-object distance (*x*-axis). Each plot represents dynamics considering only ±20 and ±40 agent-object relative positions (horizontal separations). For *left* side plots, '*sp*' and '*ep*' labels indicate where the dynamics starts and ends for each starting position, respectively. *Black dots* in *right*-side plots (*y*-axis) point out the long-term autonomous attractors for the mono- and bistable agents. Plots indicate that the bistable agent moves with different direction after sensing a leftward (-20 and -40 object positions) or rightward (20 and 40 object positions) placed avoiding object by using different dynamical states.

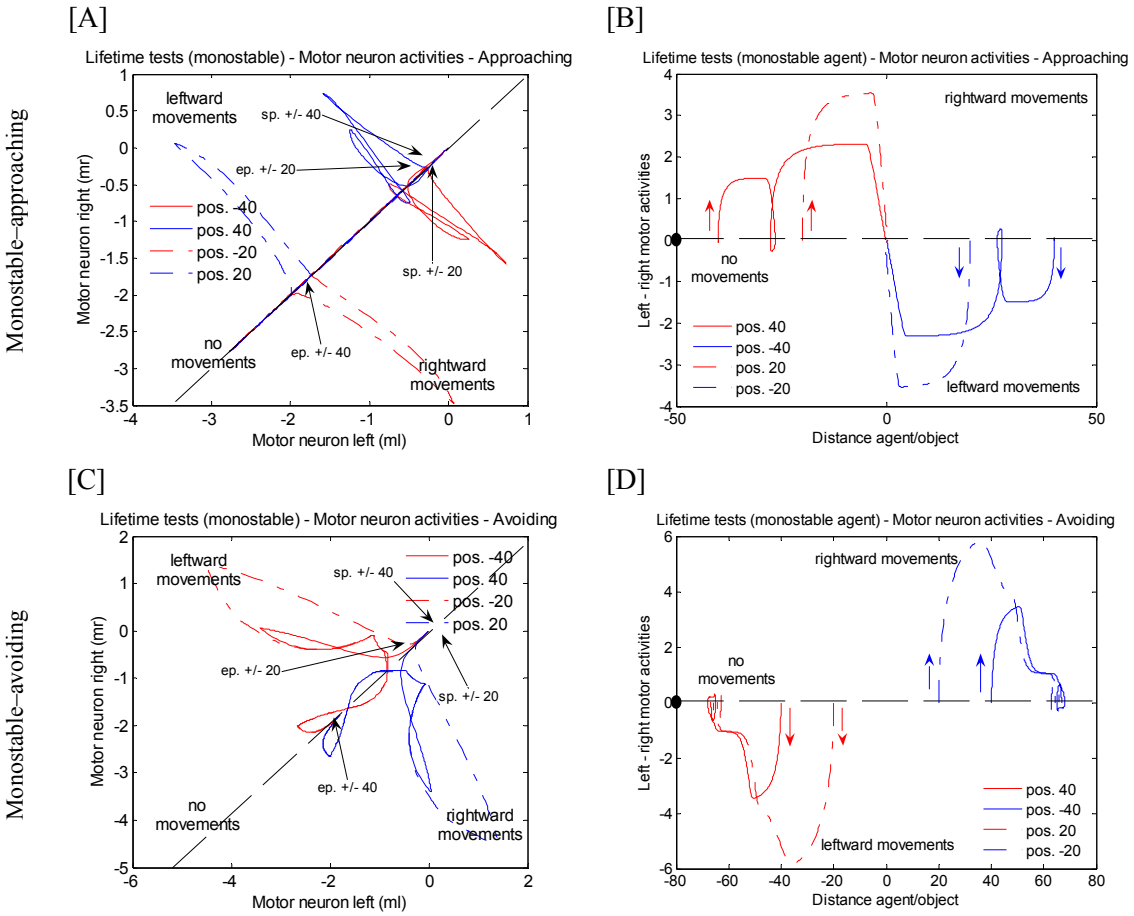


Figure 6.14 - Example of dynamical trajectories when a monostable agent is placed in the environment. Plots [A & C] represent the dynamics of motor neuron states (y_j) for a mono- and bistable agent; [B & D] indicate the dynamical relation between the difference of left (*ml*) and right (*mr*) motor neuron states (y_i) during approaching and avoiding behaviours, and agent-object distance (*x*-axis). See Figure 6.13 caption for further descriptions. Dynamics suggest that part of the monostable agent's strategy in solving approaching and avoiding behaviours is based on returning to its autonomous dynamical state when the difference in motor neuron activities is zero (dotted line). The *black dot* (autonomous attractor) indicated in *y*-axes of B & D plots represents no movements of the monostable agent.

We can now put together all the information from behavioural and dynamical analyses in order to explain the mono- and bistable strategy for categorical perception in normal situations (i.e. without perturbations). During the first half of a trial, some sensory patterns come to correlate with clear approaching or avoiding behaviours in both analysed agents, while other patterns cannot produce a qualitative change in behaviour. All through the trial midpoint, if the agent cannot match its current sensory stimuli with one that it recognizes, both agents start scanning actions in the presence of approaching objects. The dynamics of the bistable agent can end up in one of two internal states after sensing an avoiding object (moving to one direction or not moving). In contrast, the analysed monostable agent remains dynamically near its autonomous attractor all the time, requiring the presence of an object in its environment to create transient dynamics for

approaching or avoiding movements. The monostable agent shows similar behaviour-switch features to that of the analysed bistable agent, but the former returns to a single attractor in the absence of stimuli. The bistable agent can switch its dynamical state after sensing an avoiding object, but this capacity does not seem to be an advantage for producing behaviours in comparison to the monostable agent's dynamics.

A more intuitive explanation of the type of transients that both agents show is: the monostable agent bases its behaviours on chasing *a unique attractor that moves in state space due to changes in sensory inputs*, in contrast to *more structured (ordered), long-term multiple attractor states* for the bistable agent (cf. *right* and *left* plots in Figure 6.9). The monostable agent dynamics is at, or moving toward, a unique fixed-point attractor (neurocontroller level) during environmental coupling. The behaviour of the monostable agent is therefore possible by changes of neurocontroller dynamics due to fixed-point shifts toward its unique (but mobile) attractor as the sensory input changes (cf. Figure 6.9-*right* and Figure 6.14-C&D for avoiding behaviour). Therefore, we can say that the monostable agent shows 'dynamical determinacy', i.e. the continuous presence of a unique attractor that must be chased during behaviour. In contrast, movement toward one of its fixed points chiefly determine the long-term avoiding behaviour of the bistable agent, when the agent does not engage with a falling object. This happens when it loses contact with the object after avoiding movements (cf. Figure 6.9-*left* and Figure 6.13-C&D also for avoiding behaviour). The behaviour of the bistable agent is therefore possible by changes of neurocontroller dynamics due to fixed-points shift as the sensory inputs change. In this case, the bistable dynamics presents 'dynamical indeterminacy' during avoiding behaviour, i.e. the presence of two simultaneous attractors for some sensory patterns (see Figure 6.9-*left*). We can hypothesize then that the effects of some perturbations on the bistable agent's current state produces bad performance due to incorrect dynamical switches between attractors at internal control level. To explore this last point, the next section describes experiments with sensory perturbations affecting the internal state of both mono- and bistable agents.

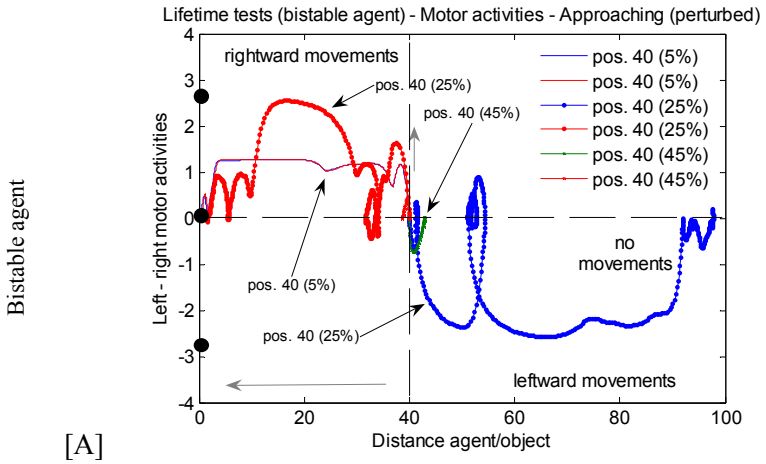
6.4.3.2 Coupled dynamics under sensory perturbations

This section show results using the same experimental scenario as that described for Figure 6.13, but after inducing 5%, 25%, and 45% of sensory noise (Figure 6.15). These percentages represent probabilities of perturbation in our tests. The algorithm induces at each time step that the current state of each binary sensor is flipped into its opposite state. For clarity, this section only reports dynamics when the agent-object relative distance is 40.

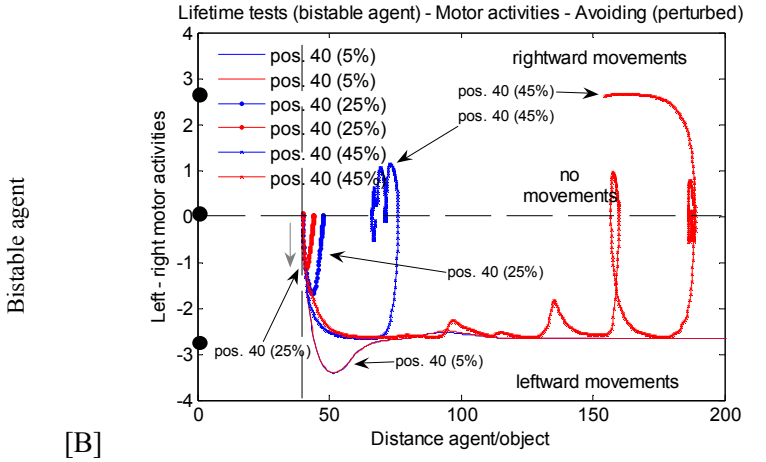
Figure 6.15 shows that the induced sensory noise differently affects mono- and bistable agents depending on the level (percentage) of perturbation. Despite the fact that the agent-environment coupled dynamics can forcefully move the inner-agent's state to different places in the state space, the dynamics of the analysed monostable agent returns to or remains near its autonomous attractor in the long run (horizontal dotted line in Figure 6.15-C & D). The monostable agent produces the

right approaching and avoiding behaviours indicated by a decrease or an increase in the agent-object relative distance (*x*-axis) in Figure 6.15-C and Figure 6.15-D, respectively. Plots of Figure 6.15 mark with light-grey arrows the dynamical trajectory that an agent's dynamics will follow in the absence of perturbations. Interestingly the monostable agent remains mostly in the same state when perturbations are relatively high (25% and 45%), showing no movements of the agent in the environment. We can observe this in the trajectories near the agent-object relative distance x=40 and around the horizontal dotted line of Figure 6.15-C & D.

The bistable agent shows internal-transient dynamics between or toward their autonomous attractors when coupled remaining dynamically in one of the two possible attractors most of the time after perturbations. These attractors are marked as black dots representing fixed-points in *y*-axes of Figure 6.15-A & B. For example, inducing 45% of perturbation (probability of noise), we can observe in Figure 6.15-B that the dynamics of the bistable agent moves to y=-2.66 when x=40, it remains near y=-2.66 up to x=170, and then it moves to y=0. However, in the end, the dynamics reaches the autonomous attractor at y=2.66. Furthermore, after inducing sensory noise with a small probability 5% of switching sensors, the dynamics moves from x=40 (y=0) to x=200 and it maintains its position mostly near the y=-2.66 (Figure 6.15-B).



[A]



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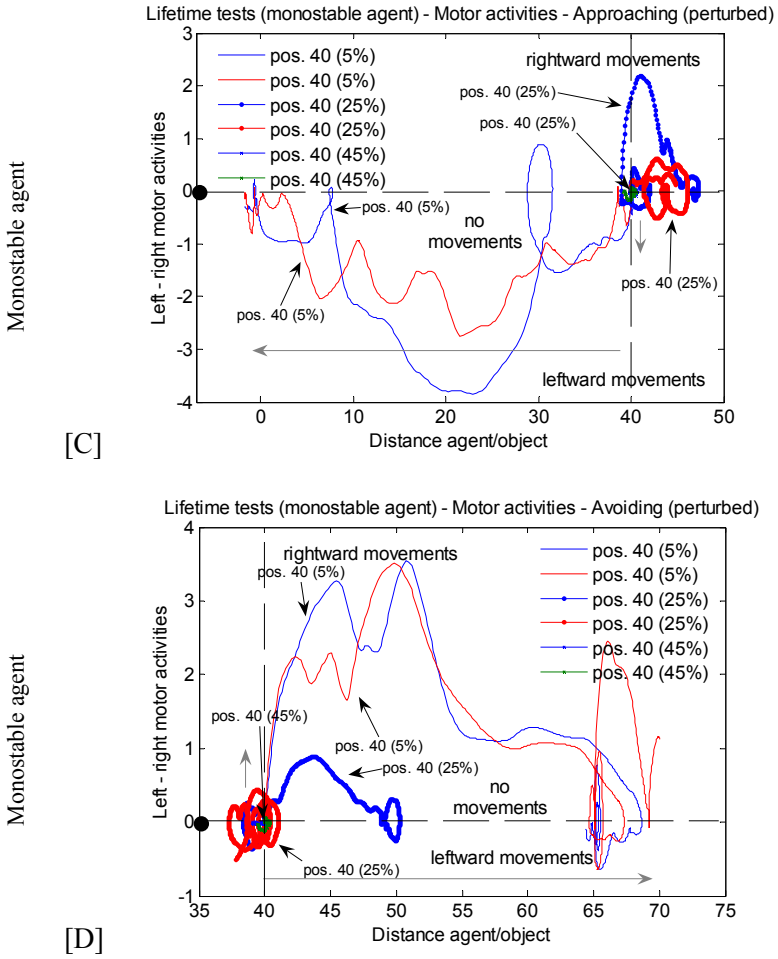

Figure 6.15 – Example of dynamical trajectories when a mono- and a bistable agent are placed in the environment after inducing sensory noise (sensor switches) with different probabilities (5%, 25%, and 45%). Plots represent dynamical trajectories of the difference between motor neuron activities (left (*ml*) and right (*mr*) motor neuron states y_j) for a mono- and a bistable agent during approaching ([A & C]) and avoiding behaviours ([B & D]) in relation to agent-object distance (*x*-axis). Each plot represents dynamics considering an agent-object relative position of 40 units (horizontal separation). *Black dots* in *y*-axes point out the long-term autonomous attractors for the mono- and bistable agents. Arrows represent the direction that the dynamic trajectories will follows in the absence of perturbation. Plots indicate the effect of stochastic processes as sensory noise affecting the transition between attractors. See main text for further descriptions.

Experimental evidence in this section indicates that perturbations that are big enough (e.g. 25% and 45%) can push the dynamics of the bistable agent to the 'wrong' dynamical state in relation to the non-perturbed scenario. In fact, in Figure 6.15-A we can observe that the effects of inducing 45% of noise produce two different dynamical trajectories for the bistable agent (i.e. toward ±2.66 or remaining around 0 attractor). In terms of behaviour, these trajectories generate approaching movements (minimizing the agent-object distance toward x=0), or leaving the agent at approximately x=97 units of distance to the approaching object's position (see labels in Figure 6.15-A). For the monostable agent, the presence of minor (5%) or major (25% and 45%) perturbations have a lower negative effect on behaviours in comparison to the bistable agent

because inner-transients in the end approach (or remain) around the agent's only attractor. The monostable agent's dynamics becomes close enough to the attractor most of the time, even when the neurocontroller presents internal transient dynamics (Figure 6.15-C & D). It is worth to note that such a 'wrong' tendency is also observed for all agents in the bistable set in similar dynamical experiments (no-reported in this chapter).

Summarizing, dynamical analyses in Figure 6.15 point towards the effect of sensorimotor perturbations as stochastic processes that negatively affect the production of approaching and avoiding behaviours mainly for the bistable agent. Such a stochasticity induces dynamical switches within the bistable agent's state space, generating for instance avoiding movements when approaching is expected at behavioural level (Figure 6.15-A). We can conclude then that the capacity of the analysed bistable agent to maintain the appropriate dynamics for categorical perception is only robust to minor sensory perturbations.

6.5 Discussion: the effect of agent's perturbed dynamics in performance

This work has reported so far statistical, behavioural and dynamical analyses of the categorical perception task described in section 6.3. The focus of discussions has mainly concentrated on the type of dynamical engagements that two randomly selected agents (a mono- and a bistable agent) produce to accomplish approaching and avoiding behaviours. Studies in absence/presence of diverse types of internal and external perturbations (e.g. mutational, sensorimotor, and neurocontroller perturbations) also complete these analyses.

Results suggest that the studied monostable agent uses the presence of objects more than the bistable agent for categorical perception, which by definition is a more distributed (behavioural) control strategy. Once more, the distribution criterion in this chapter refers to the use of coupled dynamics that emerge from the evolutionary process spanning of internal control, body and environment. This use creates control dependences at neurocontroller level for behaviours. In fact, by actively using environmental dynamics, we saw that the monostable agent exhibits approaching or avoiding behaviour via a continuous sensing of falling objects.

Explanations for the less observed behavioural robustness of the analysed bistable agent (compared to the monostable one), are rooted in the effects of perturbations on the agent's internal state, pushing its internal dynamics to the 'wrong' basin of attraction (section 6.4.3.2). This result is interesting in that it opposes the intuitive thought that an agent with more internal states (i.e. fixed-point attractors) would be more sophisticated and robust for categorical perception under certain perturbations than more dynamically simple agents. More sophisticated here means that the bistable agent could 'switch' between different dynamical modes to deal with the effects of induced sensory perturbations for appropriate categorical perception. A statistical tendency to lower robustness is also reported in this part of the thesis with a set of bistable agents in section 6.4.1. This work reports dynamical analyses for the two randomly selected agents (the same agents for the whole chapter) to exemplify how perturbations can switch the internal dynamics of

a bistable agent. It is worth to note also that some agents in the bistable set are more easily to be pushed to the wrong basing of attraction than other bistable agents in the same set. The discussion of why some bistable agents are more easily pushed to the wrong basing of attraction is not introduced in this chapter, but this comparison is planned as future work.

The lesson that this work promotes is therefore that *robustness is better understood in the context of agent-environment dynamical coupling rather than being ensured internally*. Results here suggest that the combination of agent-environment coupling, and the single-state characteristic of the analysed monostable agent enable it to cope better with the effects of most of the perturbations reported here. Such a behavioural robustness, however, is present, but less observed, in analysis with the bistable agent. The proposed lesson reinforces the idea that behavioural robustness cannot be deduced directly from internal mechanisms by themselves, a common belief in systems biology literature; rather it can be associated with the dynamics arising from the coupled internal control, body and environment.

Chapter 7

Evolving experience-dependent robust behaviour in embodied agents: a one-legged walking task under sensorimotor perturbations

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"Can a system be self-organising? No system can permanently have the property that it changes properties."

W. Ross Ashby, 1981

Chapter 5 and Chapter 6 deal with analyses of evolved behavioural mechanisms that are shaped by coupled interactions. Discussions in these chapters are mainly rooted in situatedness (section 3.2.1). We study in this portion of the thesis agents with the capacity to change feedback from their bodies to accomplish a one-legged walking task by implementing the evolution of 'sensory offsets' [Macinnes & Di Paolo, 2006] (i.e. evolutionary-defined biases that modify incoming body signals). Discussions in this chapter remark the role of embodiment (section 3.2.2) in the production of behaviours. In particular, we examine whether these agents show further dependence to their coupled dynamics than others with less feedback control. The ability to sustain behaviours is tested during lifetime experiments with mutational and sensory perturbations after evolution. Using dynamical systems analysis, we identify conditions for the emergence of dynamical mechanisms that remain functional despite sensory perturbations. Results indicate that evolved agents with an evolvable sensory offsets (or in absence of them) does not necessarily offer an advantage in resilience to sensory perturbations. However, agents using multiple sensory offsets are less affected by mutational perturbations than other sets of agents. Results in addition show that agents sensing the environment directly in a noiseless environment evolve controllers

that are highly independent to sensory stimuli, while those agents using multiple sensory offsets develop further dependence to sensory signals.

Finally, experimental evidence here leads us to suggest a dynamical systems perspective on behavioural robustness that goes beyond attractors in phase space. The behaviour of agents that are evolved with sensory offsets depends not only on where in neural space the state of the neural system operates, but also on the transients to which the internal-system was being driven by sensory signals from its interactions with the environment, nervous system, and agent body. Here the distribution criterion refers to feedback from agents' body that is processed at neurocontroller level, where such a distribution is induced via sensory offsets and sensorimotor noise. This chapter is derived from work submitted for publication (see [Fernandez-Leon, 2011]).

7.1 Introduction

Recently, Macinnes and Di Paolo (2006) have discussed the role that 'the indirect experience' of sensing the environment has to the production of agent's behaviours. They analyse the process of stimuli recognition in simulated agents and the 'meaning' that agents impose to achieve dynamical engagement. By meaning, they denote the selections that agents make from their own stimuli and therefore find their own 'reference' in how to process external information. Despite the importance of such research, we have very little idea about how an agent's own experience shapes sensory signals at the neuronal level and the effect of this shaping on robust behaviour. The majority of work in this area neither explains how these mechanisms emerge from sensorimotor interactions, nor analyses whether it promotes behaviour production and robust traits in different environmental conditions.

In von Uexküll (1957)'s terms, the selection of sensory stimuli can be seen as a process which can 'bring forth their own Umwelt', or relevance in the surrounding world of agents. This suggests that agent behavioural mechanisms can be thought as *cognitively distributed* between internal control, body, and environment. As stressed by Macinnes and Di Paolo, it is not necessary however to concentrate on how an implemented agent model acquires genuine sensory cues from the environment. The description of 'functional circles' proposed by von Uexküll (1957) suggests that a 'cue' (or functional trigger) is distributed along the entire functional circle of which the organism is a part. Functional circles are "abstract structures that tie together a subjective experience or perception (termed a *perceptual cue*) and the effect that the perceptual cue has on the behaviour of the organism (called an *effector cue*)" (ibid. from [Macinnes & Di Paolo, 2006]). It is meaningless therefore to claim that a perceptual cue resides in a particular location in the agent's milieu. The ability to walk and the feedback that the nervous system receives during walking, for example, is not localized at neural level but is fully distributed throughout the agent and its dynamics, where part of the control task is 'outsourced' to the physical dynamics of the agent [Pfeifer *et al.*, 2007].

The question that arises is *what sort of control-strategy emerges if an agent's own interactions with the environment shape its sensory capacity and its dynamics under sensorimotor perturbations.* An answer to this question has conceptual and practical interest for understanding robustness in neuroscience and body control, e.g. in the consideration of controlled walking behaviour in humans in different terrain conditions. Once more, we regard an agent here for clarity as a dynamic system perturbed by, and hence responding to, a number of environmental cues and externally induced perturbations.

In this chapter, the described ER minimal model methodology may illuminate how to answer the above question due to its relatively assumption-free paradigm [Fine *et al.*, 2007]. Studying the mechanisms that emerge can inform our understanding of what to look for in natural systems and how to build better artificial ones that regulate the conditions of their exchange with the environment [Di Paolo & Iizuka, 2008]. In sections 7.2 and 7.3, the methods and experiments are introduced. In section 7.4, we examine the consequences of results and discuss ideas that remain open.

7.2 Methods

The experimental part of this chapter first investigates how a one-legged agent model in ER can produce robust walking behaviour, controlled by a single neural network. We also examine if the tuning of sensory offsets improves the agent's behavioural robustness in the presence of sensorimotor perturbations. We use artificial evolution to synthesize an embedded recurrent neural network enabling active regulation of agent-environment dynamical exchange. Experiments then inspect whether different sets of evolved agents with and without sensory offsets can exhibit a higher (or lower) qualitative dependence to environmental dynamics, but maintaining in all cases a quantitative high performance (lifetime fitness). We have based our implementation on Beer's model software and use Mathematica's tools for our dynamical analyses.

7.2.1 Agent and structure of the environment

The one-legged insect-like agent (Figure 7.1) is used as experimental model in this chapter, which is a simplified model of the simulated hexapod agent described in [Gallagher *et al.*, 1996]. This agent model is inspired on Beer and Gallagher's (1992) (see also Beer *et al.*'s (1999), Izquierdo and Bührmann's (2008), and Beer's (in press) works). In particular, Beer (1995a) has studied three variants of his legged-agent model, differing in whether sensory feedback is continuously available, only sporadically or completely absent for the agent.

Beer (1995a) reports three different types of controllers that produce the expected walking behaviour: the reflexive pattern generators (RPGs), central pattern generators (CPGs), and mixed pattern generators (MPGs). RPGs are reminiscent of Sherrington's proposed 'chained reflex' locomotion circuits that depend on the presence of external periodic timing signals [Sherrington,

1898] (ibid. from [Gallagher, 2001]). CPGs are defined as neural networks that can endogenously (i.e. without rhythmic sensory or central input) produce rhythmic patterned outputs [Marder & Calabrese, 1996]. Finally, MPGs represent a combination of previous generators – i.e. like RPGs, MPGs can use sensory feedback when it is available to improve their operation, but like CPGs they can function in its absence if necessary [Beer, 2009]. In this chapter, we focus on RPGs requiring continuous sensory feedback from the leg's joint angle (Figure 7.1). However, we qualitatively compare the trajectory of agent leg movements to the idealized trajectory obtained from a perfect CPG without sensory input.

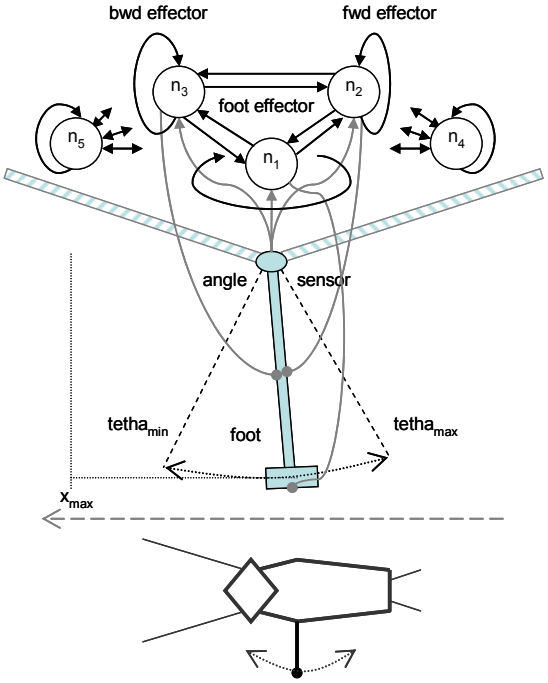


Figure 7.1 – (*top*) Schematic representation of the agent's leg configuration for one-leg walking behaviour. Neurons are fully connected including self-connections. Three effectors controls the forward and backward force applied to the leg and the foot for walking. Effectors receive sensory stimuli of the leg angle during the ongoing task. (*bottom*) The leg model of a simulated insect where the leg can swing about their single join with the body (figure based on [Beer, 1995a]).

Experiments here are based on the leg model in Figure 7.1, which has two degrees of freedom, one for rotation and another for extension. The leg can swing through 45 degrees from vertical forward (*fwd*) or backward (*bwd*). The leg passively stretches between the joint and the foot as the body translates. The agent's leg has a foot that can be either up or down. The agent's body is considered stable as long as its foot is not too far back to enable the ongoing forward motion. In order to compute the force applied to the body, the model allows a supporting leg that has passed outside of the mechanical limits to apply force in a direction that moves it back toward that mechanical limit. This is not possible in a direction that would move it further away where these

mechanical limits become one-way constraints for a supporting leg. When the leg's stability is lost, the agent falls and its forward velocity is immediately set to zero.

The leg's set-up is as follows: the leg's length is 15 units long; the maximum leg force, velocity, maximum torque and angular velocity are 0.05, 6.0, 0.5 and 1.0, in that order; forward and backward angle limits are θ_{min}=-π/6 (or -θ=-0.5236 radians) and θ_{max}=π/6 (or θ=0.5236 radians), respectively. The leg is only able to generate force over a limited angular range of motion of [-θ, θ] (see Figure 7.1). In other words, when a stretched stancing leg lifts its foot, the leg immediately snaps back to the swing angular limits of [-θ, θ]. When a stancing leg reaches these limits, forward motion comes to an abrupt stop, which according to Beer's descriptions it produces a loss of postural stability. During the stance phase, the leg stretches between the body joint and the stationary foot as the body moves with a horizontal distance between the joint and the foot. A stancing leg exceeding the angular range of motion can still provide support, but only within vertical limits of [x_{min}, x_{max}]. Torque is controlled by two motor neurons (forward or backward neuron effectors onwards). When the foot is up (*swing phase*), torque produced by effectors serves to swing the leg along an arc relative to the body [Beer, in press]. For this movement applies a limit constraint with a maximum angular acceleration of α_{max}=1/40. The binary state of the foot (*FT*) is up when the difference between effectors is lower or equal than 0.5, and down when such a difference is higher than 0.5.

The agent is given 220 units of time to walk and after this period, we measure the total walked distance during the trial (fitness measure). An agent performing a perfect walking behaviour will walk 305.7101 units of distance over these units of time, which represents more than 12 full walking steps. A successful agent must maximize the final walked distance. The overall performance of agents is averaged over all trials producing a value in range [0, 306].

7.2.2 The implemented network topologies

The agent's leg is controlled by a fully connected five-neuron controller, where three of these neurons are effectors creating the force applied to the agent's body that generates translational motion. One effector (*n1*) governs the state of the foot, and the other two generate (*n2*) clockwise and (*n3*) counter clockwise torques to the leg's single joint producing forward and leftward movements. The remaining two units are interneurons with no-specified role in the agent's leg behaviour. Only effector neurons receive a weighted sensory input from the leg's angle sensor that measures the leg's angular position in radians. The angle sensor is proportional to the angular deviation of the leg from the perpendicular axis to the long one of the body. The neurocontroller supplies signals specifying what torques should be applied at each joint. These signals are summed, and depending on the state of the leg's foot will either move the body (foot down) or rotate the leg about its joint (foot up). The motor output equation to compute the force (*f*) applied to the body for walking movements is:

*Leg.ForwardForce = NervousSystem.MotorNeuronOutput(2) * MaxLegForce*
*Leg.BackwardForce = NervousSystem.MotorNeuronOutput(3) * MaxLegForce*
f = Leg.ForwardForce - Leg.BackwardForce

The embedded controller defines one or three mutable sensory attributes (or offsets) to the agent's genotype (further explained in the next section). These offsets are either all the same or different for every sensor-interneuron connection (Figure 7.2), and are added to every sensory signal. Sensory offsets consequently act as 'biases of sensory signals' that controllers must process for motor actions after receiving sensory stimuli of the leg angle during the ongoing task. The agent is able to co-evolve to some extent the capacity to sense the environment alongside the rest of its internal dynamics in order to remain functional. By 'functional' in this context, we mean the capacity of agents to produce rhythmic stepping for the expected walking behaviour. As introduced in section 7.1, the presence of sensory offsets adds to the model the capacity that an agent can bias its sensory input based on its own interactions with the environment. The use of offsets means that we can no longer observe a signal of zero to neurons if we disrupt the angle sensor of the controller (i.e. setting the sensor to non-sensing value).

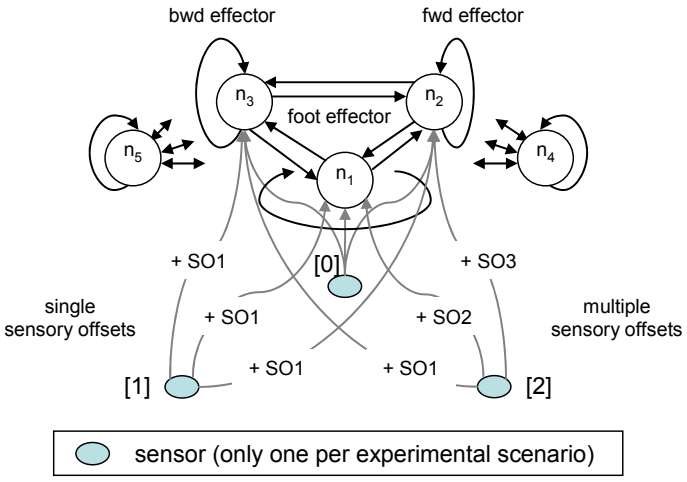


Figure 7.2 –Schematic representation of the implemented controller topology. Only one sensor is used in each experimental scenario. The signal provided by the leg's angle sensor is fed [0] directly into the controller; [1] one sensory offset (SO1) is added to every synaptic connection from sensors to connected neurons; *or* [2] it is added multiple sensory offsets to each sensory connection (SO*i*). Offsets are positive and genetically determined.

7.2.3 Agent's controller definition

A CTRNN (section 4.3.1) controls the behaviour of the leg and finally the movement of the agent. The following equations define the implemented neuron-like units:

$$\tau_i \frac{dy_i}{dt} = -y_i + \sum_j^n w_{ji} z_j + I_i \tag{7.1}$$

$$z_j = \sigma(g_j(y_j + \theta_j)) \tag{7.2}$$

$$\sigma(x) = 1/(1+e^{-x}) \tag{7.3}$$

where y_i is the activation of the *i*-th neuron (e.g. the state or 'membrane potential'); τ_i is its time constant in range [1, 10]; w_{ji} is the strength of the connection from the *j*-th to the *i*-th neuron in range [-20, 20]; θ_j is a bias term in range [-15, 15]; g_j is a gain with value 1 for all neurons; $\sigma(x)$ is the standard logistic activation function; I_i represents an external input (i.e. a signal from the sensor to which an offset will be added); n is the number of neurons in the network. Sensory offsets between the sensor and connected neurons are defined in range [-π/6, π/6] (or [-0.5236, 0.5236] radians). Incoming signals are computed as the current leg angle times a constant value of 5.0/(π/6). The controller receives then an input signal $S = SW.\phi$ from the angle sensor (ϕ value), where SW=30/π (see [Beer, in press]). To such sensor and interneuron connection, a sensory offset (*or* multiple of them per sensory connection) is added when indicated in experiments in this chapter (see Figure 7.2).

7.2.4 Artificial evolution settings

Biases, time-constants, synaptic connections and sensory offsets are evolved using a version of the microbial genetic algorithm proposed by Harvey (2001) (section 4.2), coding real valued genotypes over the range [0, 1]. Genes are linearly mapped to network parameters in their respective phenotypic ranges. The offspring of microbial tournaments replaces the loser. Offspring are generated from microbial tournaments by mutating the winner genotype and recombining with a probability of 0.6 at each locus. Gene mutation is implemented as a random displacement on every gene drawn from a Gaussian distribution with mean 0 and variance 0.2. The algorithm forces each gene to be in range [0, 1] during evolution (using reflection) and specifies a probability of 0.05 for mutating each locus.

We define a population of 40 genotypes during evolution. The number of trials, run duration and number of generations are defined as 100, 500 and 1000, respectively. A generation, in this context, is the time it takes to generate the same number of new individuals (or a new population). The algorithm calculates the neuron activations forward through time by straightforward time-slicing using Euler integration with a time-step of 0.1. The neuron's activations are uniformly

randomized in range [-0.1, 0.1] between different runs. The leg's angle with respect to the body (state of the leg) was initialised between runs at uniformly random values in range [-π/6, π/6].

7.2.5 Selection of task parameters

Before rigorously comparing the behaviour of legged agents using and not using sensory offsets, this section describes some observations during our preliminary tests in a different experimental scenario. This was made in order to understand the effect of sensory offsets on evolved agents. First, we ran an exploratory investigation with reactive and non-reactive agents performing categorical perception task [Beer, 1996, 2003]. We carried out it using zero, one, or multiple sensory offsets per sensor-neuron connection, analysing the effect on agent performance with/without self-connections at neural level, a lower number of sensors (2, 4 or 6 sensors), and/or reducing the number of interneurons from 5 to 4, 3, and 2 neurons. We proposed further experimental set-ups changing properties of falling objects (e.g. their size and shape), experimenting also with sensors that measured the horizontal distance between a falling object and agent's current position. Several attempts to evolve models with these numbers of interneurons, object properties and sensor features were unsuccessful in demonstrating advantages of sensory offsets. We did not obtain a significant difference in fitness when evolving offsets with categorical perception task. However, we obtained high performance in these tasks without sensory offsets (see Chapter 6).

These preliminary results suggested that the effects of sensory offsets cancelled each other, possibly due to the high number of synaptic connections (35 in total) in our model agent for categorical perception task. We did not continue testing whether a lower number of sensors or synaptic connections produced better performance. This was mainly because the implemented controller topology seems to be the minimum necessary for obtaining good categorical perception (see for example [Slocum *et al.*, 2000]). Our preliminary results raise the following question: how can we identify a task that produces better-adapted agents using sensory offsets? Macinnes' (2007) experiments, suggest continuous feedback seems a necessary factor when evolving successful agents with sensory offsets. Accordingly, we have proposed the analysis of walking behaviour requiring not only the production of motion, but also a continuous feedback from agent's leg position to produce the right switching movement. The following sections describe experiments with legged agents in detail.

7.3 Results

7.3.1 Statistical and sensory perturbation analyses

Figure 7.3 shows the lifetime (median) fitness performance of different sets of agents evolved with and without sensory offsets, where 10 walking agents compose each set. We have obtained

each of them from an independent evolutionary run selecting only the best-fit agent after evolution. Data points in Figure 7.3 refer to:

- (*CUE0*) agents evolved *without sensory offsets*;
- (*CUE1*) agents evolved with *one sensory offset* for all sensor-neuron connections;
- (*CUE3*) agents evolved using *three sensory offsets*, one for each sensor-neuron connection.

Each study case is differentiated into:

- (*N*) experiments with *none sensory noise*;
- (*H*) experiments with a *half level of noise*, inducing Gaussian sensory noise with mean signal 0 and variance $\pi/12$;
- (*D*) experiments with a *double level of noise*, inducing Gaussian sensory noise with mean signal 0 and variance $\pi/6$.

We compare these nine independent sets of agents in how they produce the expected walking behaviour. The performance of sets evolved without sensory offsets (CUE0) achieved 96.43%, 94.98% and 95% of lifetime fitness for N, H and D levels of noise, respectively. These percentages indicate efficacy compared to a perfect movement. The percentages for other sets are CUE1 (N) 96.89%, (H) 96.75%, (D) 68.97%; and CUE3 (N) 99.22%, (H) 93.67%, (D) 68.59%, respectively, showing that all studied cases obtain good performance in motion movements mostly in the absence of sensory noise, and also with H level of noise. When noise is relatively high (level D), only the CUE0(D) set obtain a high performance in comparison to CUE1(D) and CUE3(D) (Figure 7.3). This indicates that the presence of D level of noise represents a challenge for evolution in come up with agents that produce perfect motion (mainly for CUE1 and CUE3 sets with sensory offsets).

Results in this section indicate that *the presence of evolvable sensory offsets does not offer an advantage in resilience to noise,* as we can see in Figure 7.3. For example, CUE1(D) and CUE3(D) sets evolved with sensory offsets have worse fitness than CUE0(D), a set evolved without offsets. Sensory noise mostly has a negative effect on the mean performance of most sets of agents. Note however that CUE3(N) set obtain the highest mean performance (303.3230) evolving sensory offsets without environmental noise (Figure 7.3-C). We continue investigating some of the characteristics of these sets of agents in next sections.

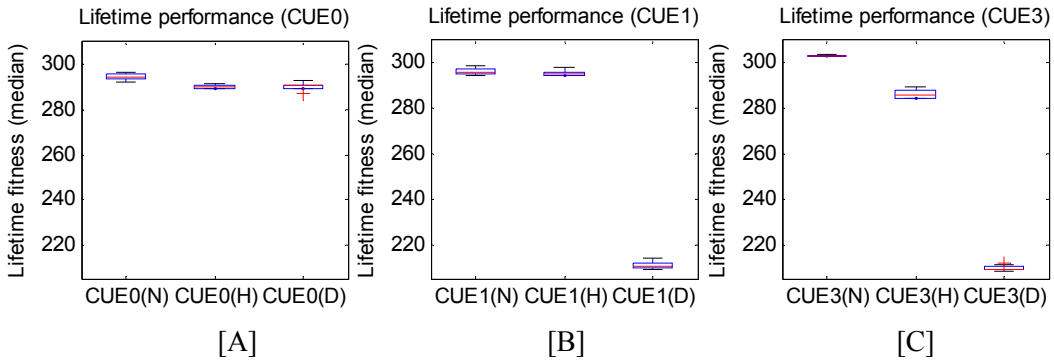


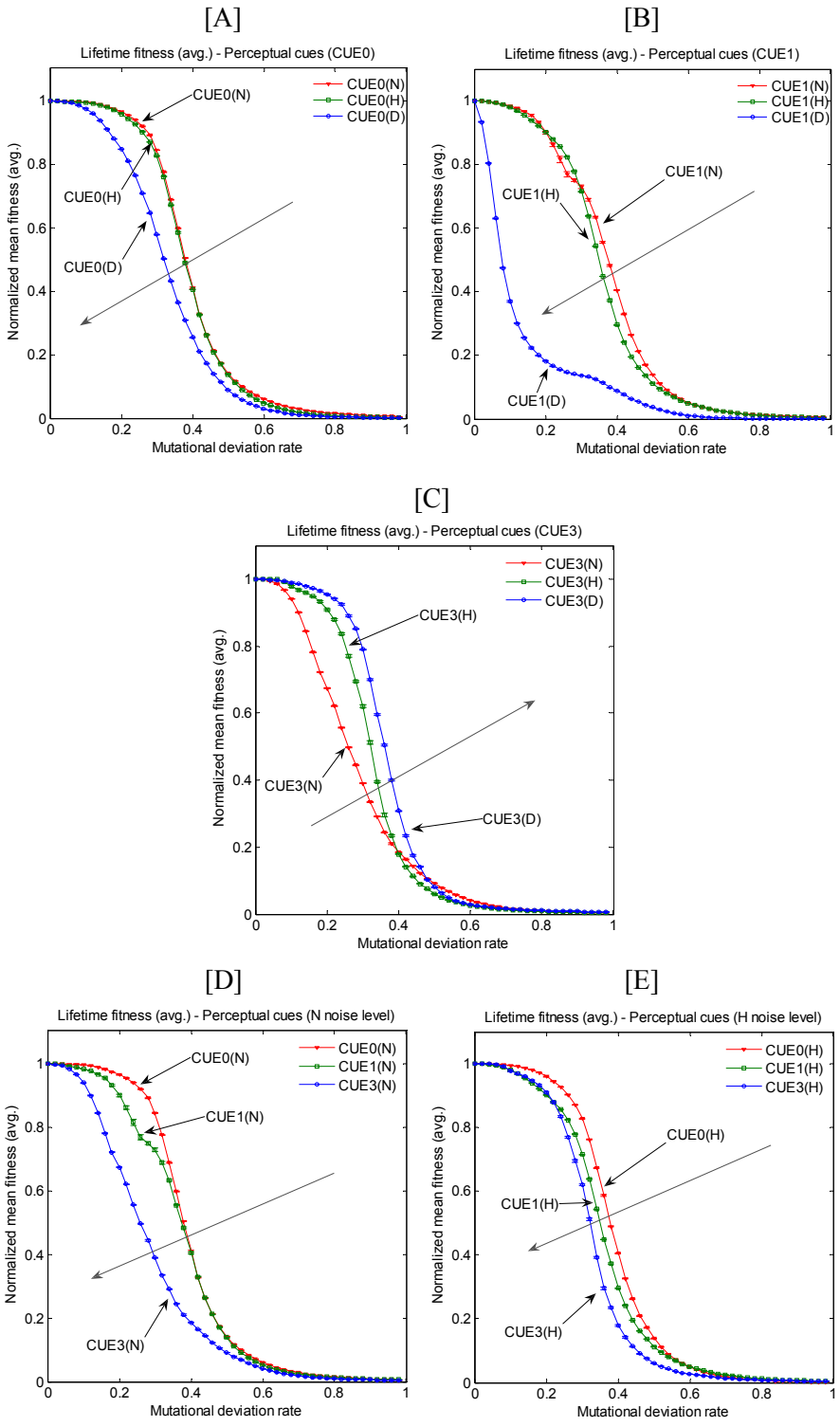
Figure 7.3 – Lifetime performance (median) obtained in tests after evolution. Box plots (25% to 75% quartiles and outliers as point) compare the fitness achieved by [A] CUE0 the control case without sensory offsets, [B] CUE1 set using one sensory offset, and [C] CUE3 set implementing multiple sensory offsets (3 in total). Each set is also divided into (N) experiments without sensory Gaussian noise, (H) experiments using Gaussian noise with mean 0 and variance $\pi/12$, and (D) Gaussian noise with mean 0 and variance $\pi/6$. Each data point (obtained afters 100 independent experiments) represents the median performance over 10 neurocontrollers. Plots show that all studied cases obtain good performance in walking behaviour; mostly in the absence of sensory noise (N) or when the level of noise is H. When noise is relatively high (level D), only the CUE0(D) set remains high performance in comparison to CUE1(D) and CUE3(D) sets of agents.

7.3.2 Behavioural robustness analyses through mutational perturbations

We focus in this section and in section 7.3.3 on studying the dependency of agents to sensory signals and the persistence of walking behaviour under sensorimotor and mutational perturbations. These perturbations are selected because agents were never exposed to failures on their sensory incomings and neurocontroller structure during evolution, and so there is not a priory reason to assume that agents will successfully cope with perturbations such as these.

Figure 7.4 represents the effects of inducing mutational perturbations on the normalised mean fitness of agent sets. Each data point represents 1000 independent experiments per agent (10 agents for each set). To every gene in an agent's genotype expression, the algorithm adds a randomly generated Gaussian value with mean zero and controlled mutational deviation in range [0, 1], and then we measure the agent's performance. Due to the low variability of every data point (<0.03), curves in Figure 7.4 present significant differences among mean performances when curves do not overlap. We can observe that the increase of mutation rate (mainly from >0.3 to 1.0 in *x*-axes in Figure 7.4), creates a degradation of the walking behaviour in all sets. CUE0 sets (namely, CUE0(N), CUE0(H) and CUE0(D)) are not seriously affected when increasing the mutational deviation rate in range [0.0, 0.3]. Sets evolved with H and D levels of noise in Figure 7.4-A show a decay in performance that seems not considerably high for mutational rates lower than 0.3. The effect of increasing such rate in sets CUE1 and CUE3 (Figure 7.4-B & C) show a

decay in performance, but this decay notoriously increases for CUE1(D) and CUE3(N) sets in Figure 7.4-B and Figure 7.4-C, respectively.



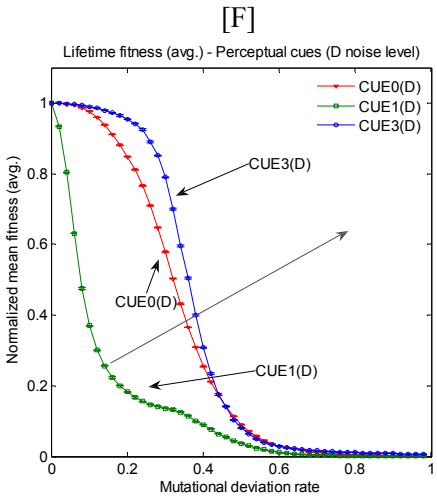


Figure 7.4 – The effects of mutational perturbations on the normalized mean performance of set of agents in tests after evolution (10 agents per set) in [A, B & C] plots. Plots [D, E & F] are re-plots of the same data for comparative purposes. Mutational perturbations add a randomly distributed Gaussian value relative to each gene with mean zero and controlled deviation in range [0, 1] (*x*-axes). Each data point represents the mean fitness obtained in 1000 independent experiments for every agent. Legends indicate sets (CUE0) without sensory offsets, sets using (CUE1) one sensory offset for all sensor-neuron connections and (CUE3) multiple sensory offsets. N indicates tests without sensory Gaussian noise, H tests using Gaussian noise with mean 0 and variance $\pi/12$, and D tests inducing Gaussian noise with mean 0 and variance $\pi/6$. Grey arrows stand for the tendency to better performance when increasing noise from N, H to D levels (plots in [A, B & C]) or increasing the number of sensory offsets (plots in [D, E & F]). Results show in [A] that CUE0 sets (i.e. CUE0(N), CUE0(H) and CUE0(D)) are not seriously affected when increasing the mutational deviation rate in comparison to other sets. Agents in sets [B] CUE1 and [C] CUE3 also shown a non-considerable high decay in performance, but this decay is noticeably and moderate high for CUE1(D) and CUE3(N) sets, respectively.

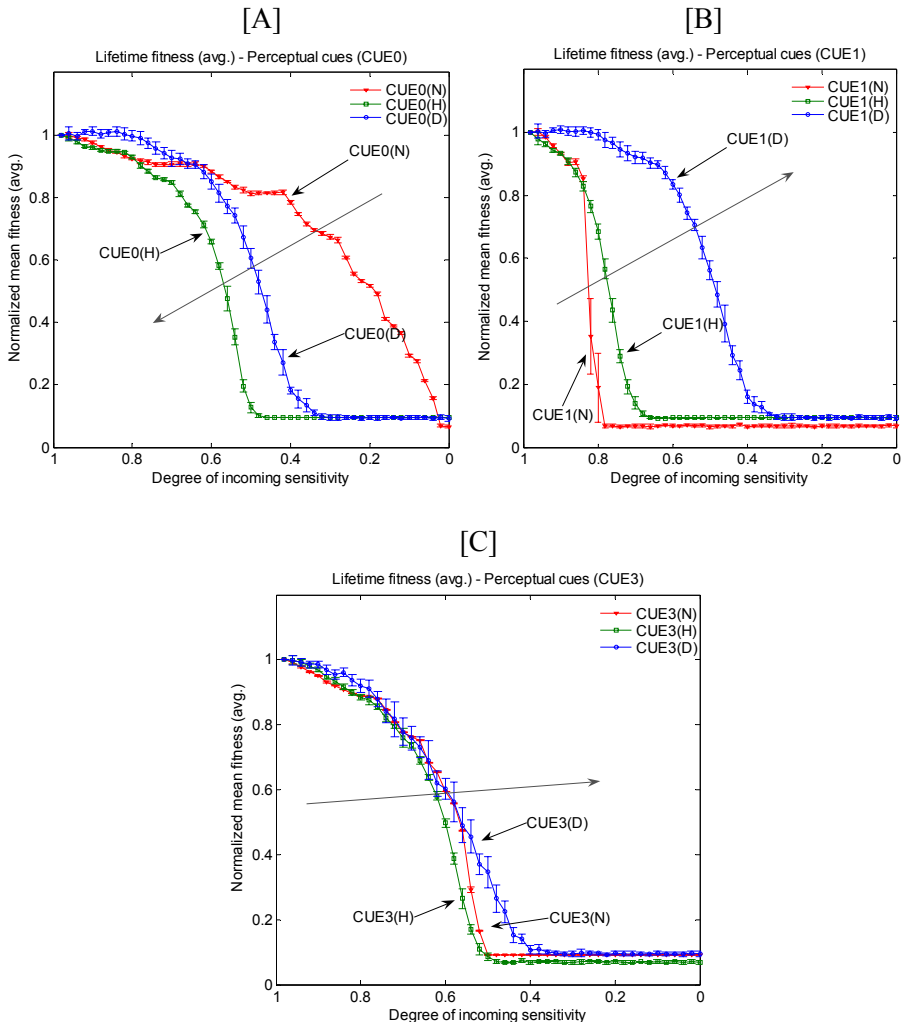
Observations agree with our preliminary supposition that one-legged agents evolved with high levels of sensory noise benefit from using differentiated (multiple) sensory offsets for walking behaviour in the presence of mutational perturbations (see Figure 7.4-D, E & F plots). Although most of CUE0, CUE1 and CUE3 sets have similar overall mean fitness, results show that randomly perturbing properties of agents through mutational perturbations has some negative effect on the overall performance of CUE0 and CUE1 sets. Agents often become slower than in the control case (without mutational perturbations) - i.e. after every step, the leg is stepping slower or the controller's ability to provide rhythmic dynamics is partially destroyed by perturbations.

Results in Figure 7.4-F also indicate that agents with multiple perceptual cues (CUE3) in the presence of D level of noise are not considerably affected by mutational perturbations lower than 0.3, in comparison to CUE0(D) and CUE1(D) sets. When we contrast the performance of CUE3(D) to CUE3(N) under perturbations, a substantial high decay of performance appears in Figure 7.4-C after disturbing the latter set of agents. This indicates that agents in CUE3(D) perturbed with D level of noise have a tendency to be more robust to mutations than other CUE3 sets. One hypothesis is that individual neurons may effectively act like filters on the sensory input, averaging over spurious sensory noise (e.g. H or D levels). As we will see in section 7.3.4

(explanations around Figure 7.6 and Figure 7.7) it seems that robustness in our model with sensory offsets comes about because offsets mean non-sensorimotor neurons are saturated, and hence less affected by noise. The next section continues with analysis of sets of agents but inducing sensory perturbations.

7.3.3 Environmental perturbations through sensory degradation

This section analyses the relation between sensory dependence and mean fitness for all sets of agents in previous sections. Figure 7.5 shows the effects of altering the amount of incoming stimuli on the overall mean performance of agent sets. The algorithm scales incoming signals using a gain in range [0, 1], where 0 represents sensor off and 1 normal sensing (*x*-axes in Figure 7.5). Each data point in Figure 7.5 indicates the mean fitness obtained in 1000 independent experiments per each agent (10 agents in every set). Again, when curves do not superimpose, the results present significant differences among mean fitness due to the low variability of most data points.



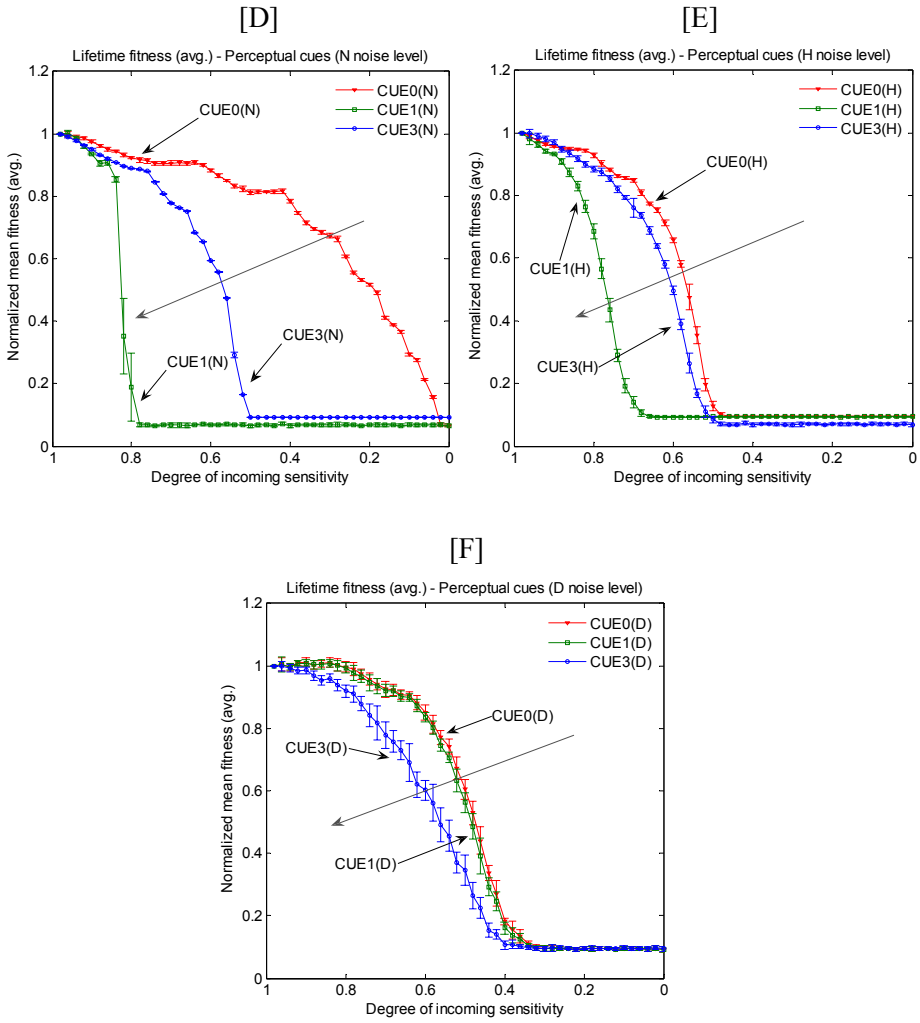


Figure 7.5 – The effects of reducing the incoming signals (sensory feedback) during tests after evolution in [A, B & C] plots. Plots [D, E & F] are re-plots of the same data for comparative purposes. Each point represents the normalized mean distance walked in a set period for decreasing the sensory incoming. Almost no difference in the agent's behaviour is observed among agent sets until the signal decreases up to 80% the current sensory range. Grey arrows represent the tendency of sensory dependence when increasing noise from N, H to D levels (plots in [A, B & C]) or the number of sensory offsets (plots in [D, E & F]). Plots in [A] indicate that CUE0(N) set presentes the highest independence to sensory signals in comparison to other sets. Contrarily, [B] CUE1(N) and CUE1(H) sets shown a high dependency to sensory incomings because their mean fitness suddenly decay for values higher than 0.7 in the controlled parameter (see main text for further details). Plots in [D, E & F] confirm that the presence sensory offsets create further dependency to sensory signals independently of the level of sensory noise as depicted by grey arrows.

Figure 7.5-A specifies that CUE0(N) set shows the highest independence to sensory signals in comparison to CUE0(H) and CUE0(D) sets. Such independence is observed as an overall better mean performance when decreasing the level of sensory signal (from 1 to 0 in *x*-axis). This result suggests that agents of such type work based on a CPG-like control strategy, because they can produce rhythmic patterned outputs with low rhythmic sensory or central input as we indicated in

section 7.2.1. However, we cannot fully associate it with CPGs due to the decay in performance in Figure 7.5-A when we perturb sensory inputs. In contrast, CUE1(N) and CUE1(H) agents in Figure 7.5-B show high dependency to sensory input because their mean performance suddenly decays for values lower than 0.8 (*x*-axis). These results indicate that CUE0(N) and CUE1(N) sets present examples of two different strategies for motion movements.

Adding higher levels of sensory noise during evolution differently affects CUE0, CUE1 and CUE3 sets (Figure 7.5). For CUE0 agents, increasing such level of noise (i.e. from N, H to D) produces more dependency on incoming signals in comparison to the control case, i.e. noiseless situation (Figure 7.5-A). For CUE1, the increase of noise augments the independence to sensory signals (Figure 7.5-B). In CUE3, changing the level of sensory noise during evolution does not produce a slight increase in the mean fitness when decreasing the degree of sensory sensitivity during lifetime (Figure 7.5-C). In other words, in the case of CUE3 sets, the increase of Gaussian noise in sensor readings (from N, H to D) produces almost no difference in the agent's overall mean fitness until the level of induced sensory degradation decays up to 60% (Figure 7.5-C). Our observation confirms that *the presence of sensory offsets creates dependency on sensory signals independent of the level of sensory noise* (as depicted by grey arrows in Figure 7.5-D, E & F). This observation also agrees with our preliminary hypothesis in that agents evolved with multiple perceptual cues sustain better performance when reducing the sensory capacity under N, H and D levels of noise. An overall observation is that the presence of further sensory noise (from N, H to D levels) produces in CUE0 and CUE1 sets a tendency toward further dependency (Figure 7.5-A) or independency (Figure 7.5-B), respectively, to sensory signals while for CUE3 it remains mostly unchanged (Figure 7.5-C).

7.3.4 Emerged neural strategies for one-leg walking behaviour

We hypothesize in sections 7.3.2 and 7.3.3 that CUE0(N), CUE1(N) and CUE3(N) agents present different dynamical strategies for motion movements. This section consequently analyses whether agents with or without sensory offsets exhibit dynamical differences at neural level based on relative high or low dependence to incoming signals. Studies here concentrate on a selected agent from each of these sets.

Figure 7.6 gives an example trial of a randomly selected agent in CUE0(N) set showing its dynamical pattern for the walking task. All neurons produce a changing output during the ongoing task in Figure 7.6-A. Figure 7.6-B indicates 'foot up' for a positive, and 'foot down' for a negative angular velocity value (states of the foot). Note that for such plot, a limited angular range of motion at leg angle ϕ_{min}=-π/6 and ϕ_{max}=π/6 is observed due to mechanical changes with limb geometry; a leg angle vertical minimum ϕ_{xmin}=-1 also appears due to modelling skeletal constraints.

As can be seen from Figure 7.6-B, the agent geometrically almost aligns its leg trajectory (dark trajectory) with an idealized optimal pattern (bright trajectory). This optimal route agrees with

results in [Beer *et al.*, 1999]. The different sections of produced dynamical pattern correspond to particular stages of the walking cycle:

(1) *foot up* and *swing*, corresponding to negative valued *x*-axis and positive valued *y*-axis;

(2) *foot down*, analogous to positive valued *x*- and *y*-axes;

(3) *stance power*, corresponding to positive valued *x*-axis and negative valued *y*-axis (where movements start from this stage of the walking cycle in reported experiments);

(4) *stance coast*, where both axes are negatively valued.

Figure 7.7 represents the dynamics of a randomly selected CUE3(N) legged agent. Despite the similarity of dynamics shown by agents in Figure 7.6 and Figure 7.7, we realize that the former agent shows a small lower performance (98.35%) in comparison to the latter one (99.22%). These percentages are taken in relation to the optimal trajectory that a walking agent can achieve (see Figure 7.3). The overall difference in the performance of these agents is in the timing of the generated leg movements; i.e. the CUE0(N) agent produces 11 rather than 12 full walk steps in comparison to the optimal case. In other words, the analysed CUE0(N) agent presents a non-optimal leg trajectory between the moment that sets its foot down in phase 2 and the instant that it starts to move the leg backwards in phase 3, where the leg is on the ground and propelling the agent forwards.

After comparing the neural dynamics controlling two randomly selected agents from CUE3(N) and CUE3(D) sets, evidence indicate that the output activity of the non-effector neurons *o4* and *o5* are constantly saturated in 0 or 1 levels. Figure 7.7-A shows an example with a CUE3(N) agent exhibiting saturation of *o4* and *o5* interneurons in 0 level of output activity. An analysis of the distribution of evolved sensory offsets for the CUE3(N) agent indicates effectively that offsets are being used, because all are positive and higher than 0.63% of the maximum offset value, i.e. θ=0.5236 radians, indicated in section 7.2.1 (see also the values of CUE3(N) sensory offset in Appendix A.4). This saturation holds also for the dynamics of a CUE1(N) agent (study not shown here). A more intuitive explanation of this saturation of non-effector neurons in our model suggests a tendency of controller dynamics to eliminate those neurons that do not intervene directly in walking behaviour. For example, the analysed CUE3(D) agent shows a non-perfectly fit foot trajectory in relation to optimal. In this case, its performance is only 69.15% of the optimal trajectory. This low performance is mainly because the CUE3(D) agent shows a non-stable walking pattern in its foot trajectory, generating around 8 instead of 12 full walking steps. In fact, its susceptibility to environmental variability (D level of noise) causes the degradation in fitness in the analysed CUE3(D) controller.

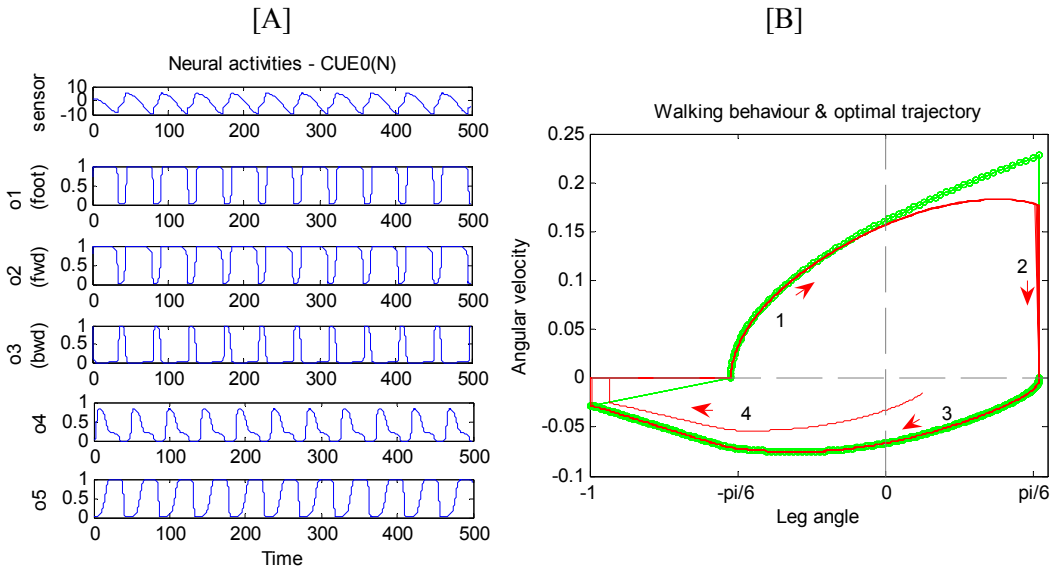


Figure 7.6 – Example trial for a randomly selected agent in CUE0(N) set. Sensory and neural activities [A] during the walking behaviour, and [B] walking dynamics in dark colour compared to the optimal walking trajectory in bright colour (circle-marked trajectory). The trajectory of the leg is represented by the leg's angle against the angular velocity related to neural activities. Plots in [B] show that the agent geometrically almost aligns its leg trajectory (dark trajectory) with an idealized optimal pattern (bright trajectory).

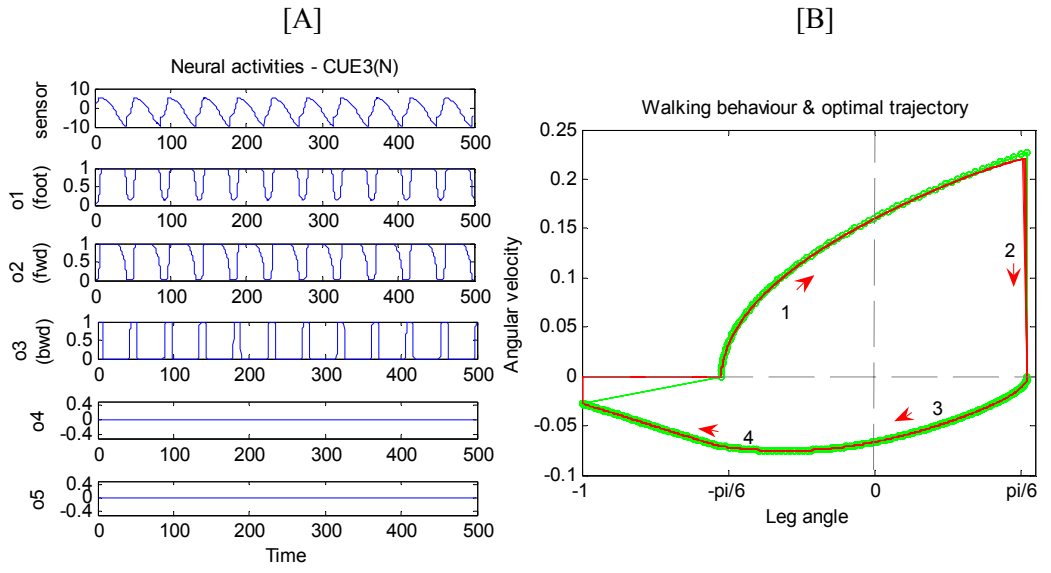


Figure 7.7 – Example trial for a randomly selected agent in CUE3(N) set. Sensory and neural activities [A] during the walking behaviour, and [B] walking dynamics in dark colour compared to the optimal walking trajectory in bright colour (circle-marked trajectory). The trajectory of the leg is represented by the leg's angle against the angular velocity related to neural activities. The saturation of non-effector neurons *o4* and *o5* in [A], suggests a dynamical tendency of these neurons to remain constant in CUE3(N) controller; i.e. they do not intervene actively in the control of the walking behaviour.

7.3.5 Transient dynamics and non-functional bifurcations

In previous sections, we have considered the dynamics of agents when coupled with the environment. These experiments are our first step towards (*a*) understanding the overall evolved control for walking behaviour, (*b*) studying the effects of evolving sensory offsets on agent dynamics, and (*c*) analysing the behavioural robustness of agents to mutational and sensory perturbations. We examine in this section the asymptotic behaviour of a randomly selected agent in CUE0(N), CUE1(N) and CUE3(N) sets (Appendix A.4 describes the structure of agents with some detail). Analyses here continue similarly as described in [Izquierdo & Bührmann, 2008] by replacing the time varying sensory input with a fixed (control) parameter that reduces our study to an autonomous dynamical system. By doing so, we can compare the coupled agent dynamics to the autonomous dynamics of controllers.

Figure 7.8 shows the long-term values, equilibria, fixed points, and periodic orbits produced by the randomly selected CUE0(N) agent as a function of the leg angle (bifurcation parameter). Where both are stable branches, we represent trajectories toward a stable point (*sp*) with a dark solid line and bright lines representing saddle point branches toward a saddle node (*sn*). Plots denote bifurcations as black dots labelled by their type. Labels stand for a fold or saddle-node bifurcation (*F*) and a local bifurcation in which a fixed point of the dynamical system loses stability (*H* or Hopf bifurcation [Strogartz, 1994]). Under reasonably generic assumptions about the dynamical system, we consider these *H* bifurcations as orbitally stable, if a certain quantity called the first Lyapunov coefficient is negative, and the bifurcation is supercritical. Otherwise, it is unstable and the bifurcation is subcritical [Strogartz, 1994].

The identification of these bifurcations is important in order to discover the probability that sensory perturbations produce non-functional bifurcations for walking behaviour in studied agents. In Figure 7.8-C & D, we can observe five bifurcations as black points at -0.598, -0.486, -0.025, 0.047 and -0.013 angle values. The black dot labelled H at angle -0.013 indicates a stable spiral point for sensor values in (-0.598; -0.013]. Other points represent saddle-node bifurcations (folds) from which a fixed point (dark lines) and a saddle node trajectory (bright lines) arise. The spiral point is a stable limit cycle (weakened) that emerges near the origin H. The size of the cycle first changes along the named sensor range crashing to a stable fold until it reverts to a stable spiral point for close values outside such range (e.g. sensor values higher than -0.013 but lower than 0.047). The generated cycle is created and destroyed in saddle-node bifurcations on a loop (Figure 7.9). In other words, the Hopf bifurcation gives rise to a branch of stable limit cycles that quickly terminates when the limit cycle touches the dark trajectory of stable point branch, and another stable limit cycle branch exists between fold bifurcations. Interestingly, we do not observe Hopf bifurcations (as evidenced by the CUE0(N) case) for the analysed CUE1(N) and CUE3(N).

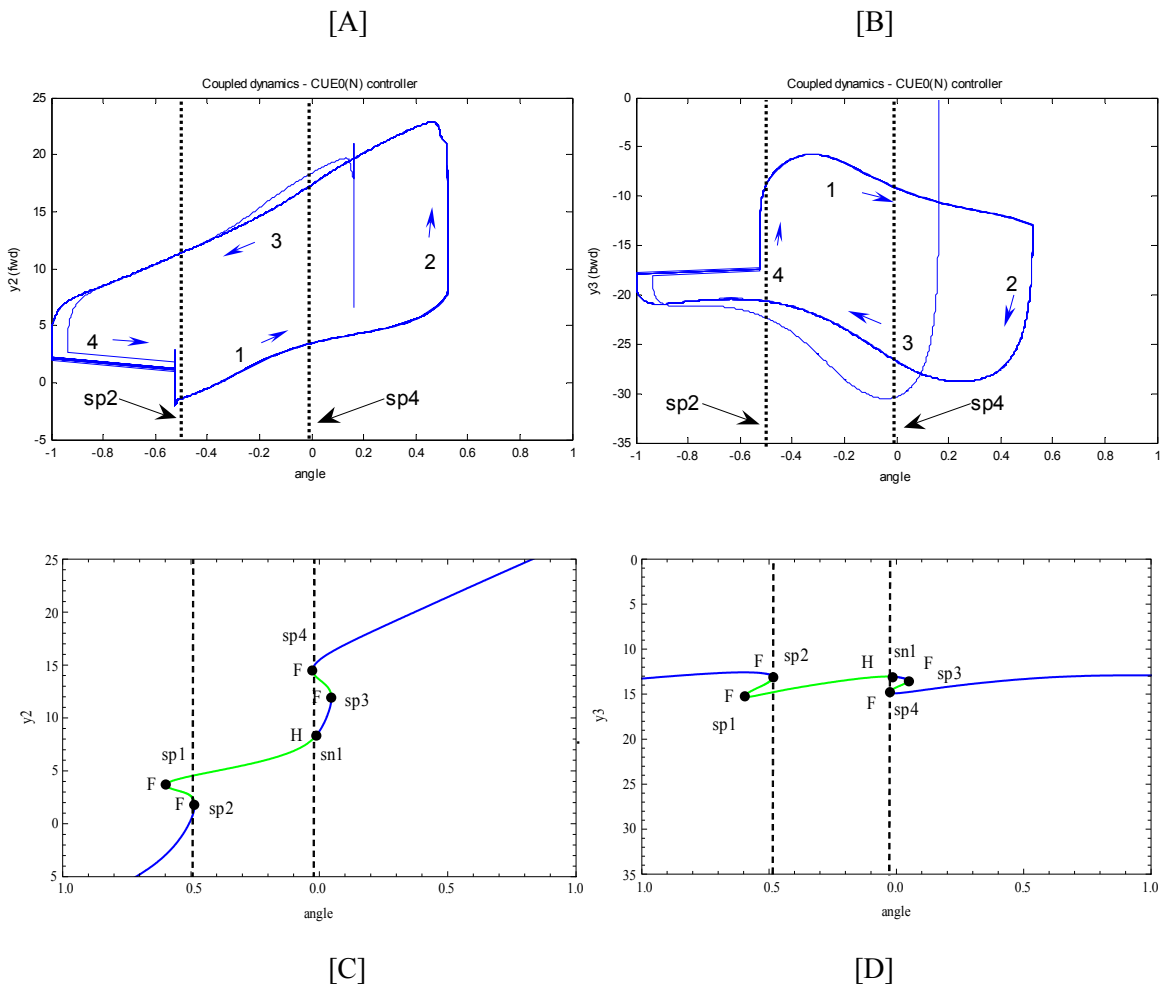


Figure 7.8 – Bifurcation diagram for the analysed CUE0(N) controller in [C & D] and agent coupled dynamics in [A & B]. Note that mostly the coupled cycle in [A & B] remains outside the dashed lines. Bifurcation diagrams represent only two-dimensional slices of the six-dimensional bifurcation space (five neurons and the sensor). The agent-environment coupled trajectories stand for two slices of the non-autonomous controller dynamics. Axes stand for the activities of effector neurons *y2* (fwd), *y3* (bwd) at *y*-axis and the leg angle sensor (*x*-axis). In [C & D] plots, bifurcation points appears at (*sp1*) -0.598, (*sp2*) -0.486, (*sp3*) 0.047, (*sp4*) -0.025, and (*sn1*) -0.013 angle values. Plots indicate that the trajectory of the CUE0(N) controller, when driven by the agent's sensor (angle), is itself influenced by the circuit's effectors. The inner dynamical cycle that arises from the coupled system is observed to switch between stable trajectories toward *sp2* and *sp4* stable points (see [A & C] and [B & D] plots overlapped).

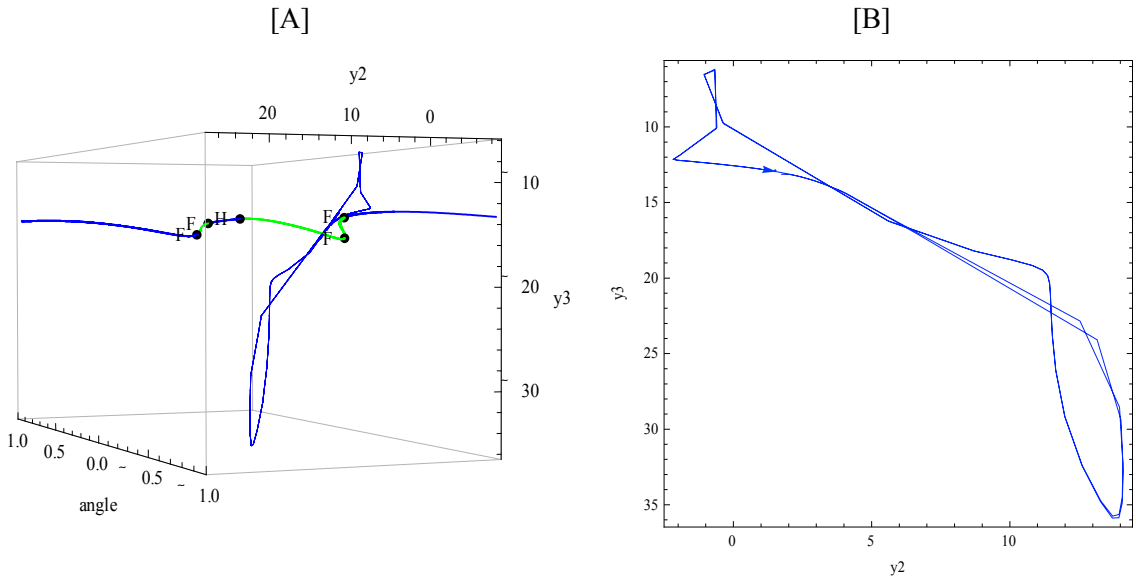


Figure 7.9 – Bifurcation diagram for the analysed CUE0(N) controller autonomous dynamics in [A]. Two-dimensional slices in [B] of the six-dimension bifurcation space (five neurons and the sensor). Axes represent the activities of neuron *y2* (fwd), *y3* (bwd) and the leg angle sensor. Trajectory depicts the stable cycle for -0.013 sensor angle value obtained after finding and following the branch of limit cycles emanating from the Hopf point. Plots represent the local internal transient trajectory that affects the global coupled dynamics between stable trajectories toward *sp2* and *sp4* stable points in Figure 7.8-C & D.

Figure 7.10-C & D and Figure 7.11-C & D show the asymptotic behaviour of CUE1(N) and CUE3(N) controllers relative to the incoming sensory signal (see bifurcation diagrams). In the former case, we can see five saddle-node bifurcations (F) at -0.652, -0.778, -0.183, -0.092 and 0.094 sensor angle values. In the following case, these bifurcations appear at -0.502, -0.209, -0.213 and -0.067 values. We then can conjecture that the Hopf bifurcation could be used for walking behaviour in the CUE0(N) strategy, but the presence of such type of bifurcation is not compulsory required by the task because it does not appear for the analysed CUE1(N) and CUE3(N) controllers.

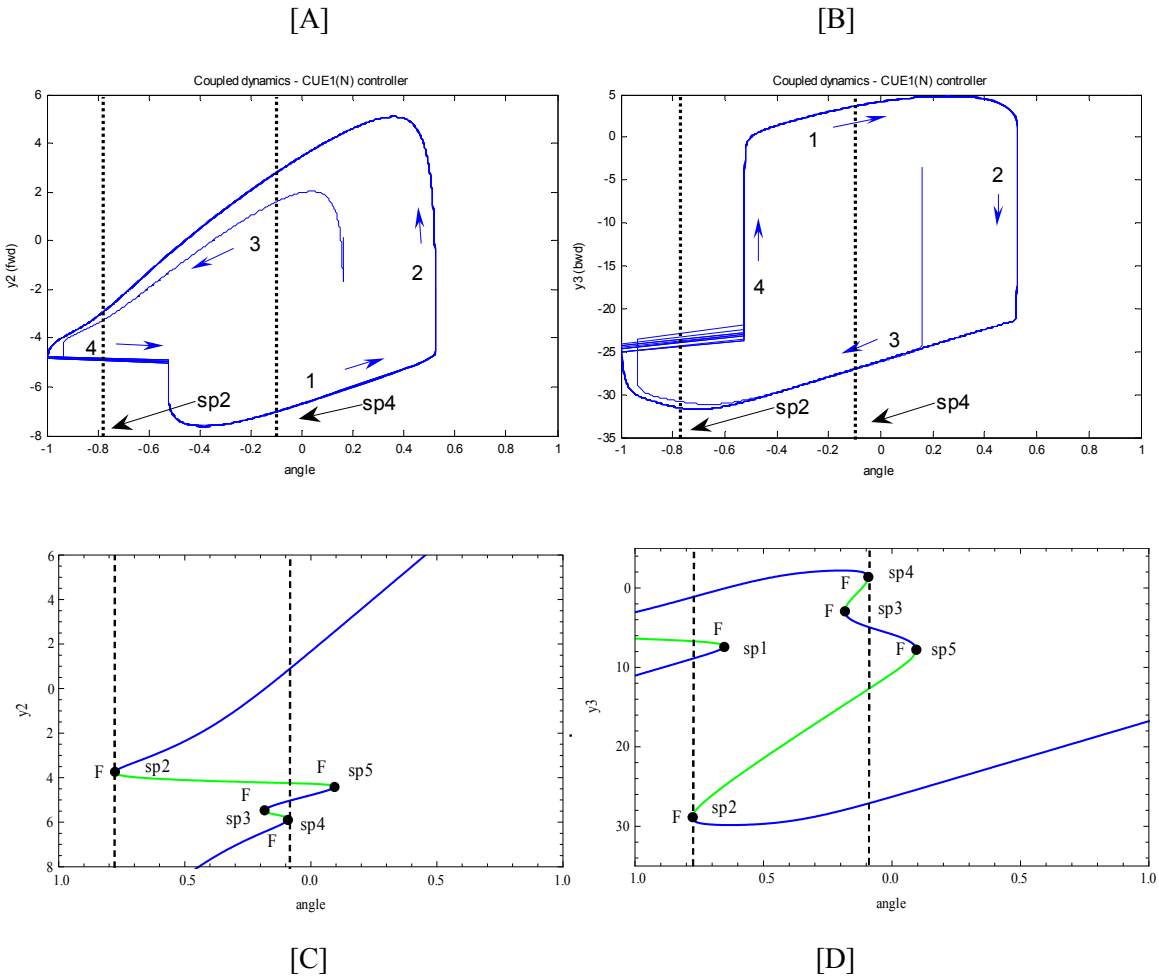


Figure 7.10 – Bifurcation diagram for the analysed CUE1(N) controller in [C & D] and agent coupled dynamics in [A & B]. Note that a great part of the cycle in [A & B] is produced inside dashed lines. Bifurcation diagrams represent only two-dimensional slices of the six-dimensional bifurcation space (five neurons and the sensor). The agent-environment coupled trajectories stand for two slices of the non-autonomous controller dynamics. Axes stand for the activities of effector neurons *y2* (fwd), *y3* (bwd) at *y*-axis and the leg angle sensor (*x*-axis). In [C & D] plots, bifurcation points appears at (*sp1*) -0.652, (*sp2*) -0.778, (*sp3*) -0.183, (*sp4*) -0.092 and (*sp5*) 0.094 angle values. Plots indicate that the trajectory of the CUE1(N) controller, when driven by the agent's sensor (angle), is itself influenced by the circuit's effectors. The inner dynamical cycle that arises from the coupled system is observed to switch between stable trajectories toward *sp2* and *sp4* stable points (see [A & C] and [B & D] plots overlapped).

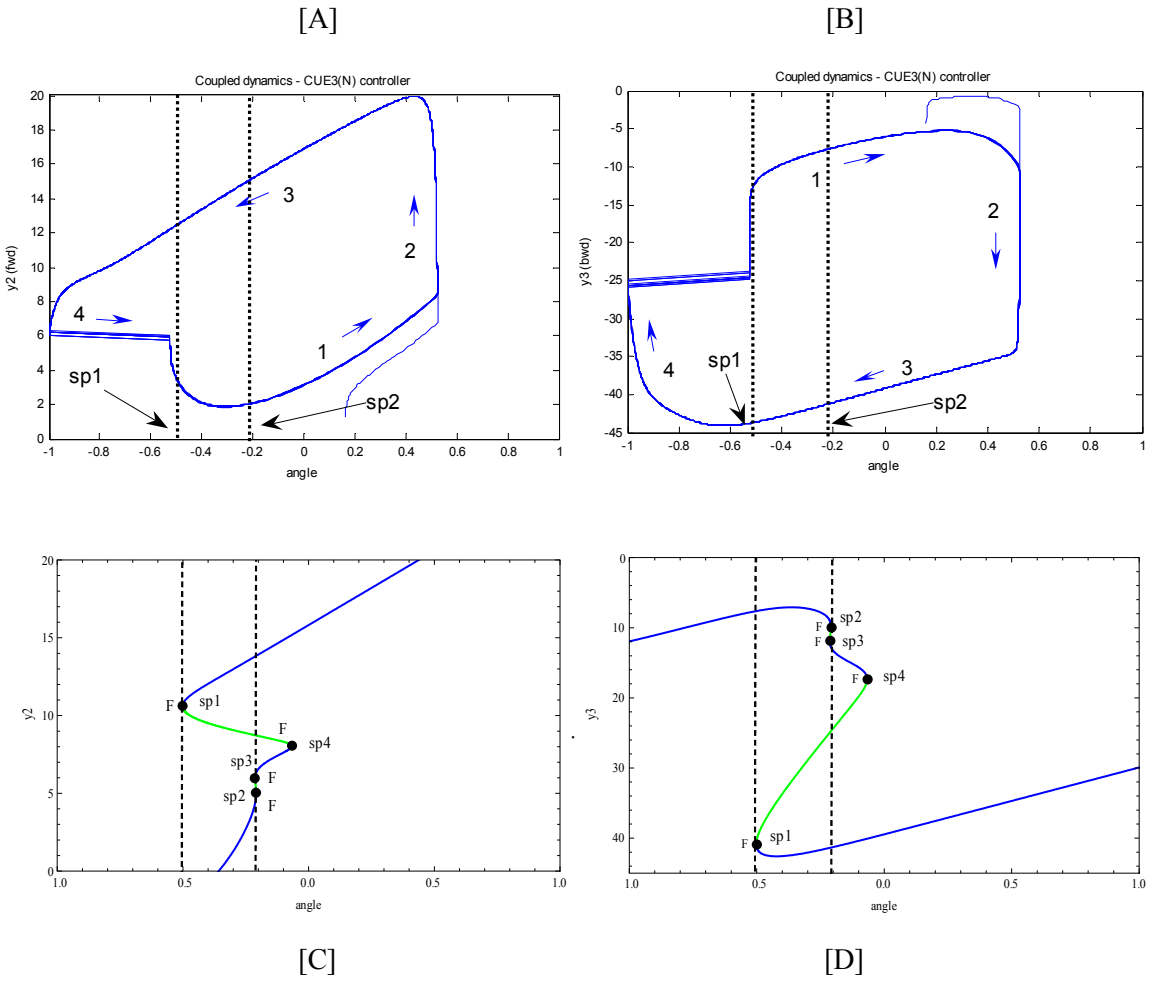


Figure 7.11 – Bifurcation diagram for the analysed CUE3(N) controller in [C & D] and agent coupled dynamics in [A & B]. Note that a great part of the cycle in [A & B] is produced outside dashed lines. Bifurcation diagrams represent only two-dimensional slices of the six-dimensional bifurcation space (five neurons and the sensor). The agent-environment coupled trajectories stand for two slices of the non-autonomous controller dynamics. Axes stand for the activities of effector neurons *y2* (fwd), *y3* (bwd) at *y*-axis and the leg angle sensor (*x*-axis). In [C & D] plots, bifurcation points appears at (*sp1*) -0.502, (*sp2*) -0.209, (*sp3*) -0.213 and (*sp4*) -0.067 angle values. Plots indicate that the trajectory of the CUE3(N) controller, when driven by the agent's sensor (angle), is itself influenced by the circuit's effectors. The inner dynamical cycle that arises from the coupled system is observed to switch between stable trajectories toward *sp1* and *sp2* stable points (see [A & C] and [B & D] plots overlapped).

In the analysed bifurcation diagrams, the size of dynamical zones that are not used to sustain walking motion varies (*x*-axis). Dashed lines in [C & D] plots in Figure 7.8, Figure 7.10 and Figure 7.11 represent these zones. In particular, we obtain that CUE0(N) and CUE1(N) cover 1.5715 and 1.8917 times more angle range (*x*-axis) than in the CUE3(N) case. The wider range of bifurcations in CUE0(N) and CUE1(N) compared with CUE3(N) case, suggests that the latter

agent has lower probability to reach non-functional bifurcations induced by sensory perturbations than the CUE0(N) and CUE1(N) cases. As we described in Figure 7.5, when perturbing the sensory feedback, we increase the probability that neurocontroller dynamics exhibit non-functional bifurcations. This difference in the covered angle range could explain in principle the relation between behavioural robustness to sensory perturbation and signal dependency that we have discussed in section 7.3.3.

The avoidance of non-functional zones suggests a shared dynamical strategy in the analysed CUE0(N), CUE1(N) and CUE3(N) controllers: *the dynamics that produce walking behaviour is mostly based on two non-simultaneous stable points in the state space of the agent's autonomous dynamics (outside dashed lines), working far from non-functional bifurcations (inside dashed lines).* In other words, dynamics inside these regions chiefly exhibit bifurcations with the potential to break walking motion. The rest of the dynamical zones (those outside dotted lines), which are used during moving, are mostly linear (represented as one stable point branch each in the controller's autonomous dynamics governing leg's movements). In this respect, we can infer why Figure 7.5-D shows that CUE1(N) agents suddenly decay in mean fitness when decreasing the sensory signal, while CUE0(N) and CUE3(N) agents remain with better mean fitness. Despite the higher probability for non-functional dynamical bifurcations, how can the CUE0(N) agent exhibit better robustness to sensory perturbations than CUE3(N)? We try to answer this question in the next section.

7.3.6 Analysis of the coupled agent-environment dynamics

Plots [A & B] in Figure 7.8, Figure 7.10 and Figure 7.11 show the dynamic trajectories of CUE0(N), CUE1(N) and CUE3(N) controllers when they are driven by the agent's sensor (*x*-axis). These dynamics depend on the self-influence of the controller effectors and sensory changes produced by agent movement. Contrasting these trajectories to the projections of the controller autonomous dynamics (plots C & D in Figure 7.8, Figure 7.10 and Figure 7.11), we can understand the dynamical differences in coupling between the three types of controllers. Note first that trajectories for pairs (*y2*; angle) and (*y3*; angle) in plot C & D of these figures follow counter-clockwise and clockwise directions, respectively. This reflects the antagonistic forward and backward forces necessary to produce the alternation of the leg phases [Izquierdo & Bührmann, 2008].

We realize that the coupled dynamics of the agent controllers do not seem to reach any stable attractor. Only when we cut the sensory incoming (autonomous system), does the dynamics converge toward the leftward attractor branch in each plot (i.e. *sp2*, *sp2* and *sp1* for CUE0(N), CUE1(N) and CUE3(N) agents, respectively), at which point agents will remain in the stance-down leg phase. During the walking behaviour of the CUE0(N) controller, for example, internal transient dynamics between stable branches control leg dynamics between *sp2* and *sp4* in Figure 7.8. A similar observation also holds for the CUE1(N) and CUE3(N) agents. By superimposing

top and bottom plots from Figure 7.8 (as well as for Figure 7.10 and Figure 7.11 independently), we can see that the coupled dynamics is constantly switching between two autonomous attractors. The CUE0(N) dynamics approaches the rightward stable attractor *sp4* (angle range [0.025, 1]) when swinging the leg forward (phase 1), moving the foot down (phase 2), approaching the leftward attractor *sp2* (angle range [-1, -0.486]) during the stance power (phase 3) and then producing leg stance coast (phase 4). The inner-system's dynamics approaches close enough to the rightward attractor *sp4* during the leg stance power, but the dynamics ends up relatively far form such attractor. The CUE0(N) controller finally depicts a trajectory toward the leftward attractor *sp2*. The last part of such leftward trajectory is directed toward the saddle bifurcation at -0.486 angle value. The trajectory however follows a shorter internal transient toward the *sp4* branch. This transient involves dynamics that are initially affected by the vicinity of the stable limit circle loop near the region where the Hopf bifurcation terminates (Figure 7.9). The transient trajectory arising from the CUE0(N) coupled dynamics, pass close the described limit cycle indeed.

The presence of a stable dynamical cycle emanating from the Hopf point in CUE0(N) controller (Figure 7.9) help to 'push out' the controller dynamics far from non-functional bifurcations in presence of sensory perturbation. This explains how CUE0(N) shows further behavioural robustness to reductions of sensory feedback in comparison to CUE1(N) and CUE3(N) agents. The later two agents do not have a similar stable cycle in their neurocontroller dynamics as we described in this section – i.e. saddle bifurcation at -0.486 angle instead, as seen in Figure 7.9.

We conclude then that the whole cyclic trajectory of the CUE0(N) coupled dynamics does not solely depend on the described limit cycle in the controller's autonomous dynamics, or other autonomous dynamic trajectories around a single basin of attraction. The transient dynamic between attractors produces the completely sensory-dependant system-cyclic trajectory. The combination of controller and coupled dynamics also holds for CUE1(N) and CUE3(N) studied agents. Additional future tests may demonstrate in more detail the association between behavioural robustness to sensory perturbations and reduced dynamical zones exhibiting bifurcations. This could imply an analysis of the phase portrait of neurocontrollers. Nevertheless, phase portraits and dynamic flows of higher-dimensional systems as the implemented 6D controller cannot be compared in many ways. We can only analyse whether two- or three-dimensional slices of the entire phase portrait exhibit direct or indirect trajectories near or toward stable points.

7.4 Discussion: the effect of sensorial adjustments in behavioural robustness

This chapter has mainly explored how one-legged agents use their experience to adjust their sensory mechanisms to produce motion under sensory noise and noiseless conditions. Initially, we have analysed different sets of agents to understand the effects of sensory offsets on coupled

behaviour. We divide our study into three main groups of agents. The first set senses the environment directly and the signals provided by the agent's leg sensor are input directly into their controllers. The second set of agents has a single evolvable sensory offset transforming the signal provided by the sensor according to agent's experience. The third set has controllers with multiple sensory offsets for the defined sensor. Interestingly, our observations suggest a positive role of sensory offsets on behavioural robustness in the presence of mutational perturbations, but require certain types of environmental complexity during evolution (Figure 7.4). We have induced such complexity as sensory noise that agents should process in order to accomplish walking behaviour.

Results indicate that agents sensing the environment directly in a noiseless environment evolve controllers that are highly independent to sensory stimuli. These agents are not easily perturbed by reductions of the incoming feedback. In particular for a studied CUE0(N) agent, only a relatively low sensory feedback (<0.3) enables the agent dynamics to leave the state of the stance-coast leg phase and initiate the swing phase. Studies around CUE1(N) and CUE3(N) agents indicate that they have a considerable dependence on sensor readings, which means that they are easily perturbed by reductions of sensory feedback. The general lesson from these experiments is that all studied agents (i.e. one agent from each CUE0(N), CUE1(N) and CUE3(N) sets) undergo sensory-induced bifurcations in tests with sensory reductions, which cause behavioural degradation if too often encountered (again, see section 7.3.5). Furthermore, we have evidenced that the coupled dynamics of neurocontrollers remain functional toward autonomous attractors in the presence of sensory perturbations by avoiding non-functional bifurcations, where the size of described non-functional regions may affect robustness (regions between dotted lines in Figure 7.8, Figure 7.10, and Figure 7.11).

In the introduction of this chapter, it is indicated that by evolving with sensory offsets agents would engage more with the environment. Reported experiments with reductions of sensory capacity (section 7.3.3) have shown that agents using offsets develop neurocontrollers with considerable dependency to incoming feedback. The interactions between the controller, agent's body, and environment give then sufficient conditions to exploit distinct regions of autonomous internal-transient dynamics for solving the one-leg walking task. Walking behaviour is consequently not the result of the decoupled internal dynamics of the controller, attributed to an attractor, or attained to a basin of attraction in the agent's internal milieu. In fact, for our study, it emerges because of the interactions between multiple attractors and basins of attraction in a sensor-dependant coupled dynamics. Results in this chapter lead us to suggest a dynamical systems perspective on behavioural robustness that goes beyond attractors of controller phase space. In particular, the behaviour of agents that are evolved with sensory offsets depends not only on where in neural space the state of the neural system operates, but also on the transients to which the internal-control-system was being driven by sensory signals from its interactions with the environment, nervous system, and agent body.

Chapter 8

Evolving functional dependencies for robust behaviour in situated agents: a historically dependent task under sensorimotor perturbations

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"No system adapts to the changing: it can adapt only to what is constant."

W. Ross Ashby, 1981

In previous experimental chapters, we analyse behavioural mechanisms that emerged from agent-environment coupling and agent interaction experience. In this chapter, we explore the role of a similar dynamical process but in a historically dependent task under sensorimotor perturbations. We propose a mobile object-tracking task (also known as two-agent interaction [Froese & Di Paolo, 2008]) and tests for behavioural robustness in two kinds of model agents (see section 8.2.3). Our analysis in section 8.3 indicates that agents' coupled dynamics must remain in internal transients to maintain the expected tracking behaviour. The results also indicate that a highly distributed realization of behaviour can be (*i*) detrimental, if it is mostly based on factors that are 'necessary' for the behaviour, or (*ii*) beneficial, if it is chiefly rooted on factors that are 'sufficient' for the behaviour. This difference depends on the effects of perturbations on such a set of factors (e.g. the presence or absence of responsive partners). To be clear, case (*i*) stands for the effects of perturbations (e.g. movement inaccuracy and imprecision) on factors required for two-agents interaction (e.g. the presence of a partner) that negatively affects the two-agent interaction as we will see in section 8.3.3. Case (*ii*) represents the situation where these factors are not compulsory for two-agent interaction in that a change in them does not negatively affect the production of interaction (e.g. when we change a responsive agent for a recorded version of it).

Accordingly, we suggest in section 8.4 that future discussions of distributed cognition should take into account that there are at least two possible modes of interpreting distributed behaviour and that these have a qualitatively different effect on behavioural robustness. Section 8.5 finally provides some implications of our study suggesting a metastable understanding of behavioural robustness. Here the distribution criterion refers to the type of dynamical dependence shown for the two-agent engagement, where environmental dependence is further induced via relatively stable to noise but sensitive to stimuli internal (heteroclinic) dynamics. This chapter is based on work reported in [Fernandez-Leon & Froese, 2010] and submitted to [Fernandez-Leon, sub. 2010c].

8.1 Introduction

The idea that cognitive behaviour emerges out of the non-linear dynamics of a brain-body-environment system has become widely accepted in the fields of situated robotics and enactive AI [Beer, 2003][Froese & Ziemke, 2009]. Related debates about the 'extended mind' and 'distributed cognition' have also been spreading through the cognitive sciences, e.g. [Clark, 2008][Hutchins, 1995] (section 3.3). More recently, it has even been argued that the essential organization defining the identity of a living organism, should itself be conceived as extended across the boundary of living tissue (see [Di Paolo, 2009]).

If the mechanisms underlying life and mind were indeed most commonly realized in such a distributed manner, then we would expect this arrangement to be generally beneficial to an agent's chances of survival. One way this benefit could be expressed is in terms of increased behavioural robustness. However, in the field of systems biology, where the mathematical formulation of a theory of biological robustness remains a key challenge, the focus has so far been on internal, often modular, control mechanisms alone (Chapter 2). Accordingly, it would be mutually beneficial for the cognitive sciences and systems biology to better understand the kind of consequences that a distributed realization of behaviour can have in terms of robustness. Our aim in this chapter is to present some modelling work that continues together with other experimental chapters in this thesis to investigate this outstanding issue.

In terms of methodology, we use an ER technique and the minimally cognitive behaviour (or 'brain-body-environment') approach as developed by Beer (2003) and others (section 3.2). We base our model on a recent piece of work by Froese and Di Paolo (2008) in which two embodied-embedded agents are evolved to coordinate their directions of movement in the presence of sensorimotor noise and under minimal conditions. The agents are placed facing each other in an otherwise empty 1D environment and are equipped with nothing but a single binary touch sensor.

Froese and Di Paolo have showed that this coordinated behaviour breaks down when one agent is challenged to move with a non-responsive 'partner' (consisting of playback of previously recorded movements). In our case, we evolve model agents on the same task, but are especially interested in those agents which can also spontaneously follow the mobile object in the second,

novel scenario (i.e. where the other agent has been replaced by a 'playback' dummy) without being specifically evolved to do so. Since this would be an example of more robust object-tracking behaviour, it would provide us with an opportunity to investigate how this type of behavioural robustness is realized by the dynamics of the underlying brain-body-environment system against unexpected environmental changes.

Interestingly, we have found that the relatively more robust agent of this particular kind is more easily evolved when additional constraints were placed on the neurocontroller during the optimization process. These constraints increase the chances that the controller operates in transient regions of its state space. An extensive dynamical and behavioural analysis of one such evolved agent indicates that, even though the target behaviour is realized by an integrated brain-body-environment system, the internal transients make the integrated system as a whole less reliant upon any one particular environmental factor in realising its behaviour. Next section describes the methodology for evolving agents in this chapter.

8.2 Methods

We adapt a simulation model used in previous work [Froese & Di Paolo, 2008][Iizuka & Di Paolo, 2007a] for our investigation. The basic setup can be described as follows: two structurally identical agents face each other in a 1-D circular environment, in which they can move left or right and detect each other by means of a single touch sensor placed at the centre of their body. The task of the agents is to move in the same direction together for as far as possible while continually interacting with each other. This task is made non-trivial by the fact that each agent has to locate the other, coordinate a common direction of movement, and then to move in the same direction, while having minimal sensory input and being perturbed by sensorimotor noise. The model and its implementation are described in more detail below.

8.2.1 Agent and structure of the environment

Following [Froese & Di Paolo, 2008], touch sensors are placed in the center of agents that are 20 arbitrary units long (Figure 8.1). When the centers of the agents are less than 20 units apart from each other, the sensor is turned on (1); otherwise, it is off (0). The simulated body of the agent is controlled by a CTRNN (section 4.3.1), consisting of three nodes including two motor neurons. The difference between motor neuron's outputs drives the leftward or rightward movements of the agent. All neurons receive weighted binary sensory stimuli during the task.

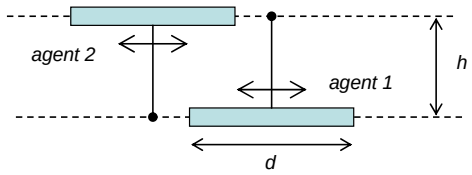


Figure 8.1 – A schematic representation to the two-agent interaction task. The two identical agents are only able to move horizontally facing each other in an unlimited continuous 1-D simulated space. Agents are equipped with a single on/off sensor at the center of their simulated bodies.

We introduce Gaussian noise in effector motor neurons and a random switch of the binary sensor of both agents. The use of random initial activations, motor noise, and sensory switches induce the agents to break the symmetry of their initial movements since their CTRNN controllers are structurally identical. This helps the agents to converge on a common direction of movement. Furthermore, the presence of noise and sensory switches during evolution increases the probability that non-recorded agents can cope with playback situations (non-interactive agents), and increases the ability of interacting agents to behave robustly in the presence of sensorimotor noise. We follow [Froese & Di Paolo, 2008] in optimising agents for highly fit coordination behaviour. In contrast to [Iizuka & Di Paolo, 2007a], the agents are not explicitly evolved to break off interaction when detecting that the other agent is a non-responsive copy.

8.2.2 Agent's controller definition

Three fully interconnected CTRNN nodes with self-connections, as defined by the following equations, control an agent:

$$\tau_i \frac{dy_i}{dt} = -y_i + \sum_j^n w_{ji} z_j + I_i . gs \tag{8.1}$$

$$z_j = \sigma\left(y_j + \theta_j\right) \tag{8.2}$$

$$\sigma(x) = 1/(1+e^{-x}) \tag{8.3}$$

where y_i is the activation of the i-th neuron (e.g. the state or 'membrane potential'); τ_i is its time constant in range [1, 100]; w_{ji} is the strength of the connection from the j-th to the i-th neuron in range [-8, 8]; θ_j is a bias term in range [-3, 3]; $\sigma(x)$ is the standard logistic activation function; I_i represents an external input; and n is the number of neurons in the network. All nodes receive the same sensory input, namely the sensor state multiplied by input gain gs with range [1, 100]. The

overall agent velocity is calculated as the difference between left and right effector neurons by mapping the outputs of these neurons onto the range [-1, 1] and multiplying them by an output gain parameter in range [1, 50]. We calculate the neuron activations forward through time by straightforward time-slicing using Euler integration with a time-step of 0.1.

8.2.3 The implemented network topologies

We obtain two different sets of controllers. First, we acquire a set of 10 standard three-node CTRNN controllers obtained as explained in section 8.2.5. For the second set (also of size 10) we introduce some additional constraints into the artificial evolution of the controllers every agent in both sets is the best-fit agent obtained in one independent evolutionary run (after 1000 generations each). The idea is to induce local (structural) instability into the CTRNNs by explicitly requiring that all nodes have excitatory self-connections, while connections between nodes must be inhibitory. The weights of all self-connections (w_{ii}) have an identical magnitude. Other synaptic strengths (w_{ij}) are constrained as follows: $w_{12} = w_{23} = w_{31} = \beta_1 < 0$ and $w_{21} = w_{32} = w_{13} = \beta_2 < 0$, where β_1, β_2, and w_{ii} are parameters under evolution.

The indicated structural restrictions are a way of obtaining heteroclinic dynamics that might facilitate the emergence of behavioural robustness as suggested in [Rabinovich *et al.*, 2006]. Mostly using a 3-node small network to illustrate the use of a Lotka-Volterra model for neuron activity, Rabinovich *et al.* indicate that heteroclinic trajectories of neural systems can be obtained via non-autonomous transient dynamics receiving external stimuli and exhibiting sequential switching among temporal 'winners' (i.e. saddle nodes). This competition between nodes in a small neural system can be evidenced as an open chain of saddle nodes connected by one-dimensional separatrices that retain nearby trajectories in its vicinity. In the phase space of the network, such switching dynamics are represented by a heteroclinic sequence, which consists of several *saddle equilibria* or saddle cycles and several heteroclinic orbits connecting them, i.e., many separatrices [Strogatz, 1994]. The sequence can serve as an attracting set if every semistable set has only one *unstable* direction. To account for the existence of a heteroclinic trajectory, we can verify the eigenvalues of the Jacobian around one specific point in state space verifying that one eigenvalue has a negative and the other two have positive real and complementary imaginary parts (see section 8.3.1 for an example rooted in our experiments).

Imposing structural restrictions into CTRNN controllers is not a common practice, but some of our exploratory investigations (experiments no reported here) have revealed that we thereby increase the chances of evolving agents with robust internal transient trajectories (i.e. heteroclinic trajectories [Strogatz, 1994]), at least in their decoupled dynamics. These dynamics are relatively stable against high frequency perturbations (e.g. environmental noise of the overall spatio-temporal network), while simultaneously retaining high sensitivity to low frequency change (e.g. the same dynamical pattern may become different over time) [Rabinovich *et al.*, 2006]. The addition of our constraints is a necessary but not sufficient precondition for inducing such

transient dynamics. This is because the evolutionary process can still lead to a variety of dynamical strategies to produce behaviours in our model (e.g. using multiple fixed-point attractors at neurocontroller level). For a detailed discussion of the conditions for generating heteroclinic dynamics see [Strogatz, 1994].

8.2.4 Artificial evolution settings

We evolve the biases, time-constants, and synaptic connections using a version of the microbial genetic algorithm proposed by Harvey (2001) coding real valued genotypes over the range [0, 1]. Genes are linearly mapped to network parameters in their respective phenotypic ranges. The offspring of microbial tournaments replaces the loser. We define the creation of offspring of microbial tournaments as a mutation of the winner genotype with a probability of 0.6 of recombination at each locus. The gene mutation is implemented as a random displacement on every gene drawn uniformly from a Gaussian distribution with mean 0 and variance 0.2. We forced each gene to be in the range [0, 1] during evolution, reflecting back any excess at the gene boundaries. We define a probability of 0.05 for mutating each locus of the genotype.

8.2.5 Experimental procedure

For each type of controller, we evolve populations composed of 40 genotypes. The number of trials, trial duration, and number of generations are set to 25, 500 and 1000, respectively. Because we use a microbial genetic algorithm, a generation represents the iterations it takes to generate the same number of new individuals or a new population. Each trial run consists of 50 units of time (500 Euler time steps). At the start of each trial, agents have their internal neural activations set to small random values drawn from a standard uniform distribution in range [-0.1, 0.1]. For each Euler time step, we define a probability of 0.05 for switching the current sensory state into its opposite state. In other words, sensory nodes stay switched for a particular time step only if a randomly generated, uniformly distributed variable in range [0, 1] is lower or equal to 0.05 value. This procedure is repeated for every time step and it holds for all experiments reported in this chapter (otherwise specified in each section).

The initial distance between the agents is a control parameter in our simulations, where agent ‘down’ (or agent 2) always is placed at position 0 and agent ‘up’ (or agent 1) starts at a different position for each trial (25 randomly distributed different position across range [-30, 30]). Since the two agents are started in opposite orientation (‘up’ and ‘down’), it *is not* possible for the evolutionary algorithm to ‘hard code’ any trivial solution such as having the agents always move to the same direction. We also added a small perturbation to the motor outputs at each time step drawn from a Gaussian distribution with 0 mean and deviation 0.05. The motor noise is applied to the outputs of motor neurons before calculating the difference between them, and before the application of motor gains.

For every trial, we compute the fitness as the distance the agents manage to travel together by comparing the location of their final tactile contact with their starting position. The overall fitness for a solution is set to the smallest score obtained for any of the trial runs during the evaluation. In other words, in order to increase the agents' behavioural robustness against motor noise, sensory switches, and the variations in initial conditions, only the lowest score achieved in any of the trials is chosen as the overall score.

8.3 Results

We obtain 10 best neurocontrollers for each type (set) of network topology in 10 different evolutionary experiments. Considering a randomly selected starting position in range [-15, 15], the mean fitness in tests after evolution for the normal and the structurally constrained CTRNN sets obtain an average performance higher than 95% over 100 experiments. These two sets are then extensively tested, where agent 'down' (agent 2) is always placed at position 0 and agent 'up' (agent 1) starts at a different position in arena for each trial (randomly placed agent 1 at 25 positions with normal distribution across range [-30, 30]). We repeat each trial 100 times. The mean fitness score across initial conditions indicates that agents in both sets satisfactorily sustain the two-agent interaction task when both agents are responsive to interactions. The mean fitness score for agent 1 is plotted in Figure 8.2 for (*left*) the control case and (*right*) the structurally restricted case sets. Agents of both types are able to maintain the required interaction behaviour well in the range that they were originally evolved to interact, namely range [-20, 20]. Beyond this range, the fitness score is in general low for both sets. The movements of agent 2 during interaction starting at position '-11' are recorded for future tests with a playback, non-responsive agent 2.

We also ran a series of behavioural tests with perturbations relating to experimental conditions that the agents has not encountered during the optimization process. We call these situations 'extreme perturbations'. We test the behaviour of agent 1 that evolves to interact with responsive agents during evolution with a non-interactive, 'playback' agent 2. The playback agent represent the movements of an interactive agent 2 obtained from the original tests for each individual in both sets. The agents in the constrained CTRNN case are able to cope with non-responsive agents. However, agents in the control case set are not able to produce the required behaviour in the non-interactive condition (Figure 8.3).

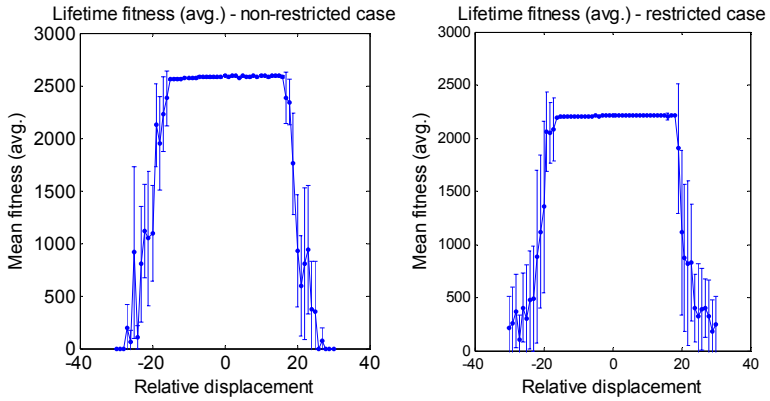


Figure 8.2 – Mean fitness performance for tests after evolution with a responsive agent 2. Results are shown starting the agent 1 from various initial positions in range [-30, 30]. From *left* to *right*, plots represent the mean score by ten fittest agents for the control case and structurally restricted case sets, respectively. Vertical bars represent standard deviations. Plots indicate that agents in both sets are able to maintain the required interaction behaviour well in the range that they were originally evolved to interact, namely range [-20, 20].

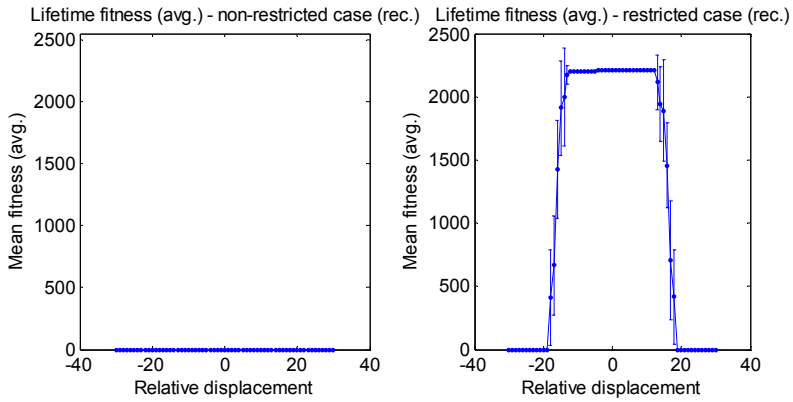


Figure 8.3 – Mean fitness performance for tests with perturbations after evolution with a non-responsive (recorded) agent 2. Results are shown starting the agent 1 from various initial positions in range [-30, 30] and for 100 independent tests per controller. The recorded agent represents the movements of an interactive agent 2 obtained from the original tests for each controller of both sets. Vertical bars represent standard deviations. From *left* to *right*, plots stand for the mean score by ten fittest agents for the control case and structurally restricted case sets, respectively. Plots indicate that agents in the control case set (*left*) are not able to produce the required behaviour in the non-interactive situation.

8.3.1 Phase portrait analysis using decoupled controllers

We study the decoupled dynamics of two randomly selected neurocontrollers from each set, namely *C1* from the standard CTRNN set and *E2* from the constrained case. Decoupled dynamics occur when the controller receives a fixed incoming signal from its sensor rather than a time-varying sensory input. We intend to observe the controller's asymptotic behaviour and finally its autonomous (decoupled) system dynamics. This first study will help us to better understand the behavioural and dynamic strategies in both agents. Since the sensory input is a binary incoming signal, for which it can be treated as a fixed parameter during this analysis. We focus on the outputs of motor neurons o_2 and o_3 in relation to input changes.

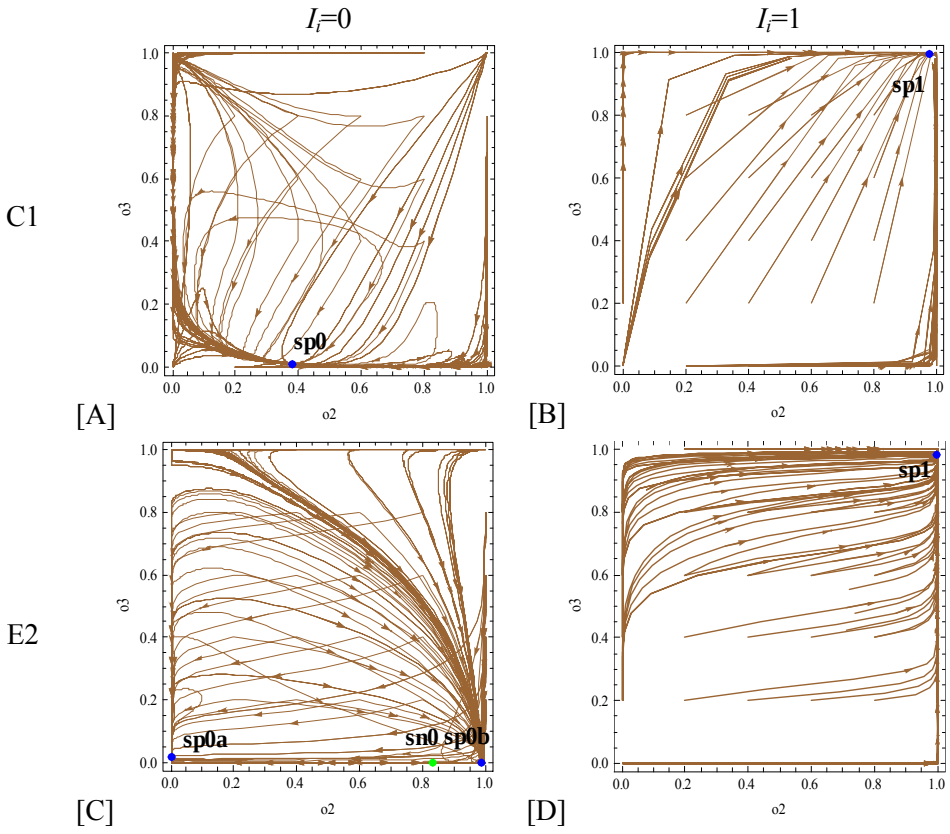


Figure 8.4 – Example of phase portraits for two-dimensional slices of the 4D phase portraits (3 neuron + sensor) of the two motor neuron outputs o_2 (leftward) and o_3 (rightward) of the C1 (*top row*) and E2 (*bottom row*) controllers. Axes represent motor outputs. *Left column* (A & C) represents phase portraits with I_i=0 and *right column* (B & D) depicts portraits for I_i=1. Labels *sp* represent stable points and *sn* saddle-node.

We fix the sensor to $I_i = 0$ or $I_i = 1$, and analyse the geometric representation of the typical trajectories in the state space of controllers (phase plane) based on motor outputs o_2 and o_3. For controller C1, the two-dimensional slices of the phase portrait show direct and slightly converged

trajectories toward one autonomous attractor (Figure 8.4-A & B). Interestingly, for the E2 controller with $I_i = 0$ (Figure 8.4-C), the dynamic flow does not connect the two stable attractors *sp0a* and *sp0b* with the saddle node between them (*sn0*). An analysis of E2's stability matrix of the *sn0* point (Figure 8.4-C) reveals the presence of a heteroclinic trajectory around *sn0*, where the eigenvalues of the Jacobian are one negative (-0.1972) and the other two are positive valued in their real parts and complementary in their imaginary parts (0.0765 ± 0.0561i) (see [Strogatz, 1994] for technical details). This analysis confirms the existence of a heteroclinic trajectory as described in section 8.2.3.

8.3.2 The coupled agent-environment system

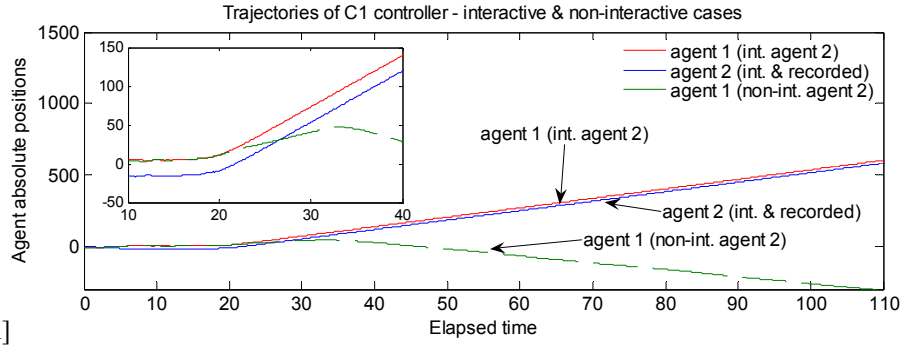
Both the C1 and the E2 controller can enable an agent to coordinate and sustain an interactive behaviour with another responsive agent. However, the two controllers differ in their response to a non-reactive playback 'partner'. Only the E2 controller can sustain an interaction with the moving object under these conditions. Because we are here interested in behavioural robustness (rather than on the ability of discrimination), we will concentrate on how E2 sustains the interaction in both situations. For comparative purposes, we will also identify the mechanism that enables C1 to discriminate agency.

Figure 8.5 shows an example of the spatial trajectories of C1 and E2 agents with an interactive and non-interactive agent (see legends). Agent 1 and agent 2 of both types interact when they cross each other trying to maintain actively contact within a relative distance of 20 units (arbitrary units). Agents move to one direction and appropriately control their leftward- and rightward velocities. Typically, the C1 agent 1 places as 'top agent' keeping its position on the positive side of the environment maintaining at the left side of agent 2 (Figure 8.5-A). E2 agent 1 all the time behaves as a 'down agent' interacting with the agent 2 from the right side (Figure 8.5-B). In particular, if the E2 agent 1 receives sensory stimulation I_i=1, it moves rightward going far agent 2's position. After this movement, the E2 agent 1 starts a curve leftwards when it stops to receive stimuli from agent 2 (I_i=0). This ongoing change of stimulation and direction enables the interaction behaviour. Both agents maintain their relative position at the boundary of the defined interaction range for making sensor contact, namely around 20 units of distance to each other.

We observe that for the C1 agent 1 case, the interaction with a recorded agent 2 is initially possible (time step < 20), but from time step 20 onwards it breaks (Figure 8.5-A). The E2's behaviour distinguishes from the C1's behaviour in that the former performs slow and large rightward and leftward movements when agents start interacting (range [45, 110] in Figure 8.5-B). In the later controller, only fast right and left movements are observed in the overall behaviour (Figure 8.5-A). Although there are significant differences in the early stages of interaction, both agents move constantly going far from the initial position when interacting with a responsive agent 2. However, as we previously introduced, eventually the C1 agent 1 moves away when it interacts with a non-responsive agent 2 (imprint plot in Figure 8.5-A). This breakdown of

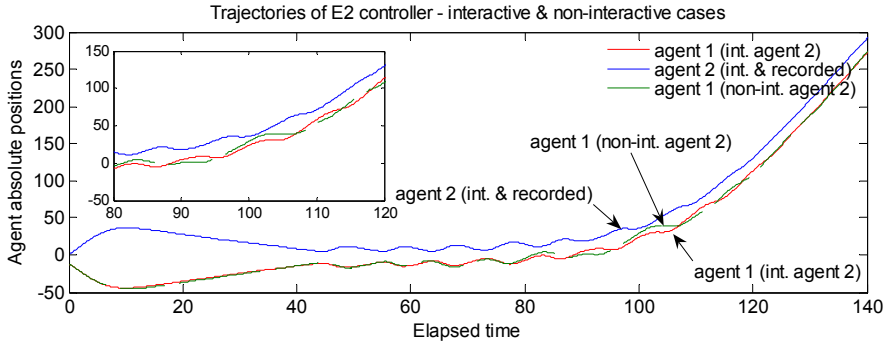
interaction happens despite the fact that trials with interactive and non-interactive agents both start from the same initial conditions of internal and body states, though they differ in the applied motor noise and sensory switches.

C1



[A]

E2



[B]

Figure 8.5 – Example of C1 and E2 trajectories (agent 1) with an interactive and non-interactive agent (agent 2). Solid lines show the results of coordinated behaviours starting from position -11 under the interactive situation. The dashed line in each figure represents the trajectories of a C1 (A) and E2 (B) agent 1 interacting with a recorded agent 2 (see captions). Tests include sensory switches (0.05) and motor noise (5%). Plots indicate that the ongoing interaction in C1's case breaks because of accumulation of sensory switches and motor noise. This break is less probable for the E2 case.

We can thus hypothesize that the ongoing interaction in C1's case with a recorded partner breaks because of accumulation of sensory switches and motor noise. Noise would normally be addressed by mutual coordination, but in this case, it appears to eventually overwhelm the single C1 agent 1, thereby generating the differentiation of behaviours when it drifts away. This conclusion is based on tests not shown in this chapter (see also [Froese & Di Paolo, 2008][Iizuka & Di Paolo, 2007a]). It is worth noting that if agents separate too much, the trial fails as the accumulation of error, which in turn produces agent separation, leads to the agents becoming non-functional (i.e. agents are not capable of actively sustain two-agent interaction). However, this hypothesis does not explain how the E2 agent is able to maintain its interaction in both of these

scenarios. What dynamic mechanism enables its behavioural robustness against such perturbations? How does it relate to the motor noise and sensory switches?

8.3.3 Tests without sensor and motor noise

Figure 8.6 shows the effect of the absence of sensory switches and motor noise for both agents with similar experimental conditions than for Figure 8.5 but for different positions of agent 1 (range [-20; 20]). In the case of the E2 controller, Figure 8.6-D shows that without sensory switches (NS) the (median) interaction performance with a recorded agent decays considerably in comparison to the control case situation (C), while the absence of motor noise (NM) does not produce decay in performance. This indicates that the E2 agent 1 can make use of the sensory switches for performing the interaction task in the non-interactive case (because of random deviations in agent's internal dynamics produced by sensor switches). Furthermore, in Figure 8.6-A, we can see that the absence of sensorimotor perturbations (NS&NM) leads to a low, but significant increase in the median performance of the C1 agent 1. This shows that the C1 agent does not use the effect of perturbations for the interaction task. It is worth noting in Figure 8.6 that notches display the variability of the medians between samples, and the width of a notch is computed so that box plots whose notches do not overlap have a 95% confidence that the true medians differentiate.

Accordingly, we conclude that the E2 agent's strategy of coping with a non-responsive agent actually makes use of the random sensory switches to produce its interactive behaviour. This strategy is not seriously affected by the accumulation of motor noise. As shown in Figure 8.6-C, the C1 controller cannot make use of sensory switching in this manner. Only the E2 agent exploits the presence of sensory switches to interact with a non-interactive partner, while C1 necessarily depends on the stimulation of a responsive agent in order to produce interactive behaviour. In sum, whereas for C1 the responsive partner agent forms a necessary and sufficient environmental condition for sustaining its tracking behaviour, for E2 the presence of a responsive partner is sufficient but not necessary because the sensory switching is also sufficient for interaction.

However, how does the E2 agent use the effects of sensory switches to create the mobile object-tracking behaviour in both of these situations, even though the non-responsive condition had not been encountered during the evolutionary process? What are the underlying dynamics of this increased behavioural robustness? This topic is the focus of discussion in the rest of this chapter.

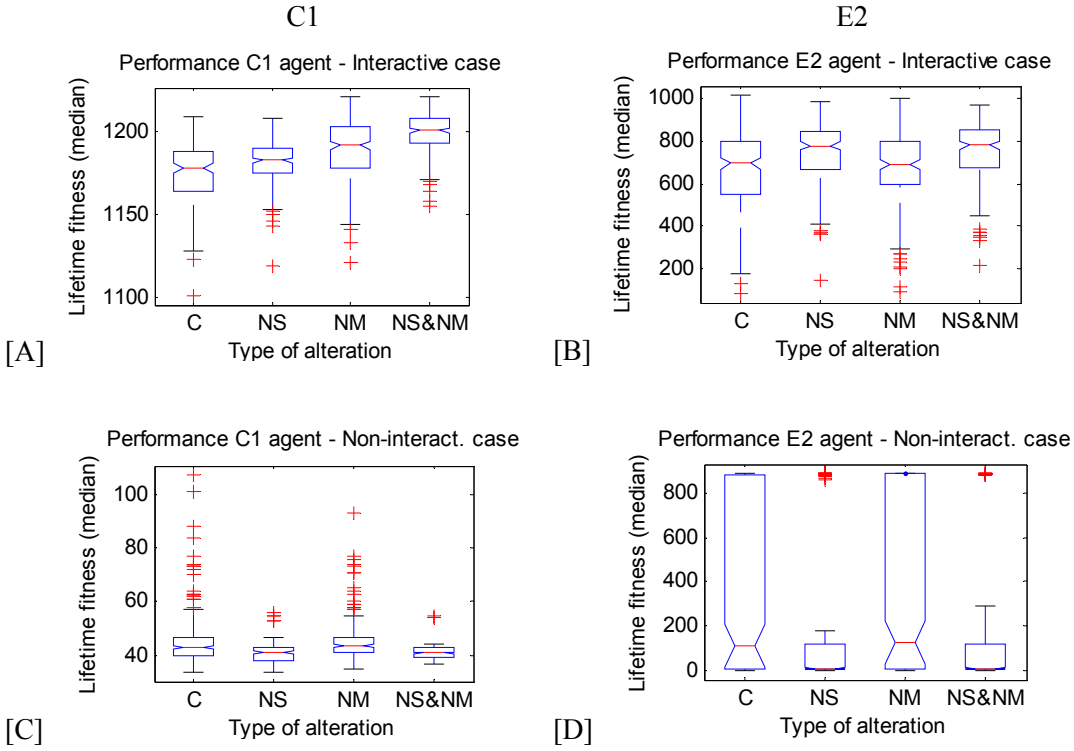


Figure 8.6 – Experiments in the absence of sensory switches and motor noise for the C1 and E2 agents. Whisker plots (25% to 75% quartiles and outliers as points) comparing the median fitness achieved by agents under each situation. *X*-axis in each plot refers to (C) control case with sensory switches and motor noise, (NS) non-existence of sensory and (NM) motor perturbations, and (NS&NM) the absence of both perturbations. Plots indicate that whereas for C1 the responsive partner agent forms a necessary and sufficient environmental condition for sustaining its tracking behaviour, for E2 the presence of a responsive partner is sufficient but not necessary because the sensory switching is also sufficient to maintain the interaction with a recorded partner.

8.3.4 Analysis of the coupled dynamics

Figure 8.7 and Figure 8.8 show examples of the neural dynamics of the motor neuron output for the C1 and E2 agents respectively during 200 units of time. Plots in the right column of these figures represent neural outputs across the time. Plots in the left column indicate the motor neuron state-space dynamics of the coupled agent-environment system for two-agent mutual interaction (*top row*) and the playback condition (*bottom row*). For ease of reference, the attractors and dynamics for the decoupled controller are also shown; namely, when the input is forced to be constantly activated (1) or deactivated (0). In both controllers, the globally attracting stable points are placed at A (I_i=0) and B (I_i=1). Results are obtained with sensory switches (0.05) and motor noise (5%).

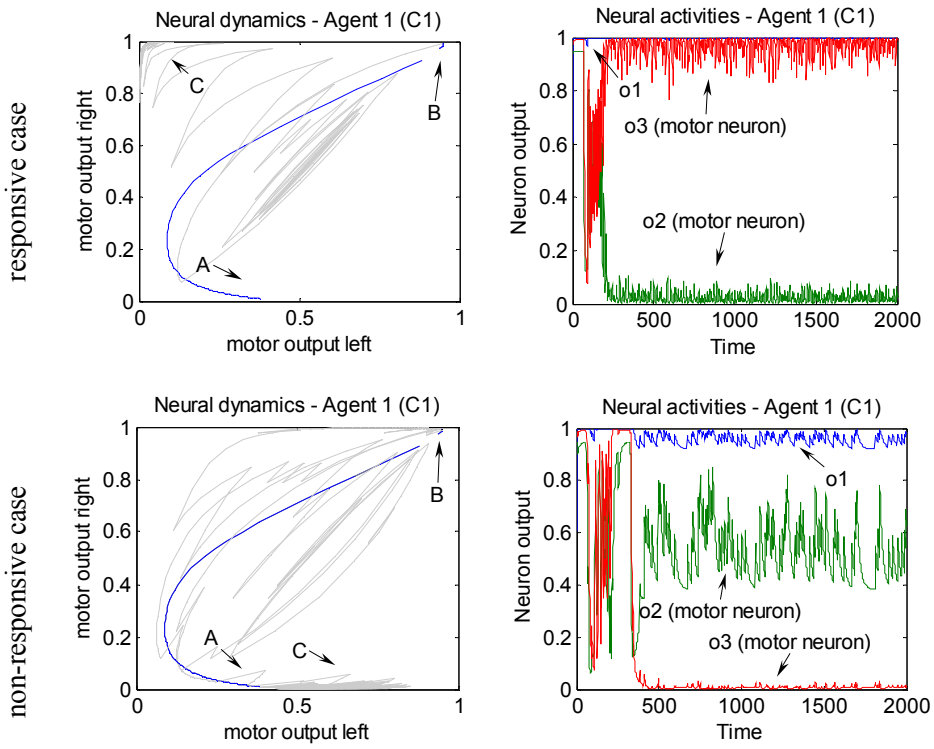


Figure 8.7 – Example of the motor neuron output (σ_i) trajectories for the C1 agent 1 during 200 units of time under normal noisy conditions. Agent 1 starts from position -11. The plots represent the coupled agent-environment dynamics of the C1 agent 1 in terms of the state space of its two motor neurons (*left column*), and the temporal progression of neural activities for the controller (*right column*). Activity is shown for the normal case when the other agent is responsive (*top row*) and when it is a non-responsive 'playback' object (*bottom row*). The globally attracting stable points are placed at labels *A* (I_i=0) and *B* (I_i=1). Left side plots also show motor neuron outputs working in transient and finally falling into one stable transit (C region). Plots indicate that the breakdown in interaction that occurs for the C1 agent when a non-responsive partner faces it is clearly visible in terms of the drastic difference in its internal dynamic pattern.

Figure 8.7 and Figure 8.8 indicate that C1 and E2 agents, in the long run, use the edges of motor neural outputs to produce interactive behaviour. The dynamics of the coupled motor neurons initially stays between the autonomous attractors and suddenly changes in direction. These changes indicate that the neural output of motors work as a discrete inner-system mainly because of the binary sensory stimuli. Note that the frequent changes of motor neurons' dynamics suggest the presence of fast responses to sensory switches that is more evident for the C1 agent than for the E2 one. Only during the final part of the interaction with an interactive agent (and for E2 interactions with a non-interactive one), do the dynamics of motor neurons reach a stable state but remaining in transient near *C* when the input changes (cf. Figure 8.7 and Figure 8.8). In fact, in this case the situatedness and embodiment of the agents during the ongoing interaction produces an inner-system with dynamics working in a transient between autonomous attractors. In other words, the dynamics of both agents remain between the autonomous fixed points (when I_i=0 and

I_i=1), and the leftward/rightward behaviour of analysed agents is caused by the fixed point shifting as the sensory input changes. A decoupled controller, in contrast, would fall into one global attractor and remain there without change.

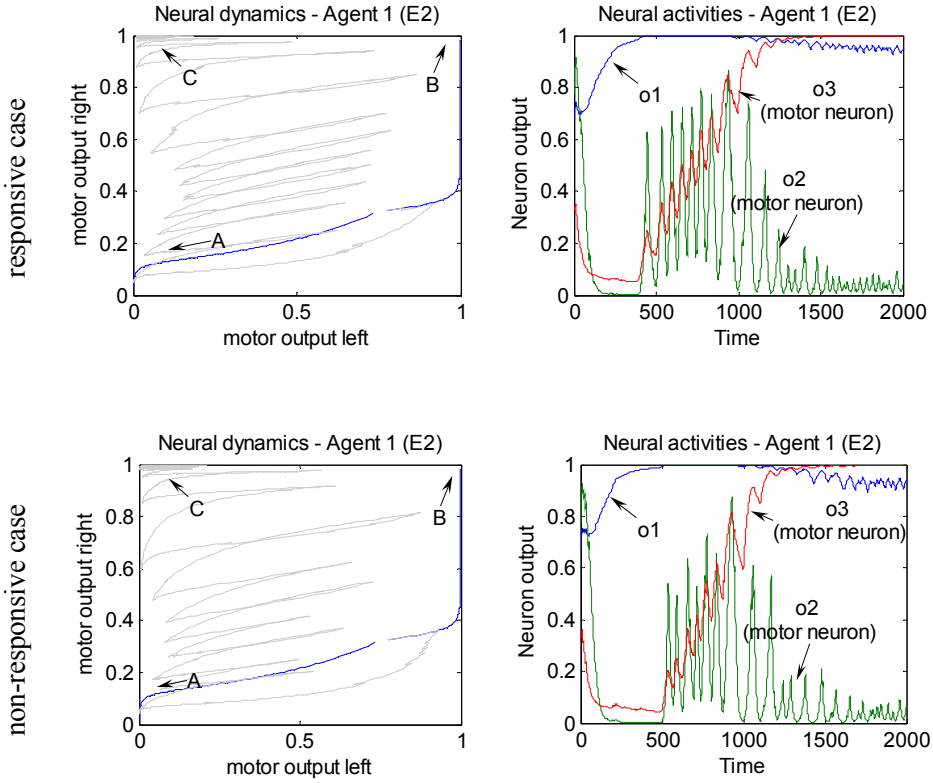


Figure 8.8 – Example of the motor neuron output (σ_i) trajectories for the E2 agent 1 during 200 units of time under normal conditions. Agent 1 starts from position -11. The plots represent the coupled agent-environment dynamics of the C1 agent 1 in terms of the state space of its two motor neurons (*left column*), and the temporal progression of neural activities for the controller (*right column*). Activity is shown for the normal case when the other agent is responsive (*top row*) and when it is a non-responsive 'playback' object (*bottom row*). The globally attracting stable points are placed at labels *A* (I_i=0) and *B* (I_i=1). Left side plots also show motor neuron outputs working in internal transient and finally falling into one stable transit (C region). Plots indicate that the dynamic pattern of the E2 agent remains qualitatively the same under responsive and non-responsive conditions, as expected from its more robust behavioural performance.

Note also that the breakdown in interaction that occurs for the C1 agent when a non-responsive partner faces it is clearly visible in terms of the drastic difference in its internal dynamic pattern (compare Figure 8.7 *top* and *bottom rows*). However, the dynamic pattern of the E2 agent, on the other hand, remains qualitatively the same under responsive and non-responsive conditions, as expected from its more robust behavioural performance (see Figure 8.8 *top* and *bottom rows*).

What we still do not know is how sensory stimuli modulate the transient dynamics of C1 and E2 differently, so as to enable the E2 controllers to maintain their dynamic pattern under both of these conditions.

8.3.5 Study of the input frequency effect and conditions for coupling behaviour

In order to get an idea of how changes in sensory input modulate the activity of the two controllers we report in this section the effects of input frequency on neurocontrollers decoupled dynamics (Figure 8.9). When either of the controllers receives inputs that have a similar frequency to the one found during the normal coupled agent-environment situation, we can observe somewhat similar dynamics as those presented in the coupled conditions of first-row plots in Figure 8.7 and Figure 8.8.

More specifically, we follow test descriptions in [Iizuka & Di Paolo, 2007a], for instance by changing the length of the stimulations of the sensory input (D) and increasing the gaps between stimuli (W) (Figure 8.9). Indeed, this generates similar motor neuron outputs working in transient between autonomous attractors and finally falling into one stable transit regime at C dynamical regions as in Figure 8.7 and Figure 8.8. These 'C regions' represent areas in the motor activities of controllers where the speed through motor output space is lower compared to the high frequency of induced (or interactive) sensory switches. Consequently, C regions are those generated from the interaction process, rather than being produced by a concrete dynamical structure at controller state space (e.g. a quasi-periodic dynamical trajectory or a limit circle). A similar, but more intuitive scenario can be represented as follows: avoiding the idea that two ping-pong players can commit a mistake during a game, we have more chance to see the ping-pong ball in a common region (i.e. in the middle point between the position of players) if the speed of interaction of these two persons increases over time. This common region in our simple example represents an analogy to C regions in our model as being generated by the frequency of sensory input during two-agent interaction.

We further observe that for the C1 agent 1 dynamics a sufficient low W and D length of the consecutive stimulus (e.g. (2; 2)) produces fast change in the agent internal dynamics settling it around the top-left corner of Figure 8.9-*left*. Increasing twice the length of the stimulations D over the temporal gaps between stimuli W (e.g. (20; 10)) also generates a dynamical tendency toward such state region but the agent's dynamics converges slower. We observe then that these combinations of (D; W) approximate relatively well to the dynamics in Figure 8.7-*top row*, indicating that these input frequencies induce similar motor dynamics.

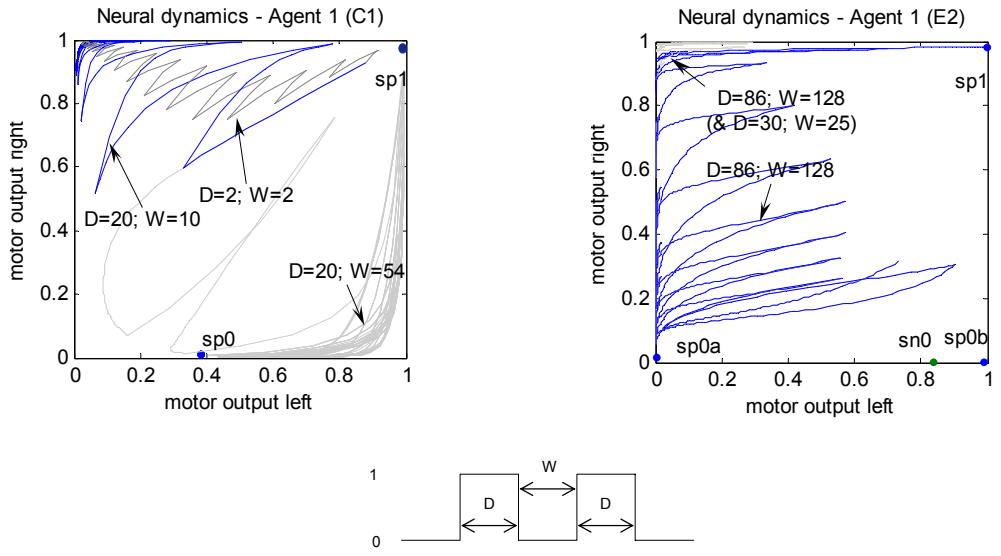


Figure 8.9 – Example of the motor neuron output (σ_i) of C1 (*left*) and E2 (*right*) agents corresponding to different sensory (periodic) stimulus (see labels). The length (D) and the gap (W) between activations and deactivations of the controlled sensory stimuli represent different sensory patterns. Tests lasted for 200 time steps. Labels *sp0a*, *sp0b*, and *sp1* indicate autonomous stable points with I_i=0 and I_i=1, respectively; *sn0* stands for a saddle node for the I_i=0 case. See main text for a description.

Contrarily, in our attempt to replicate the E2 coupled dynamics (Figure 8.9-*right*) in a similar manner, we find that it is not possible to accomplish this while using only a single combination of (D; W). Interestingly, we have to approximate the normal interaction's long-term dynamics by (stable transient regime at C zone) applying two different styles of stimulation one after the other (e.g. (86; 128) and (30; 25) in Figure 8.9-*right*). This suggests that there may be two different, clearly differentiated dynamical regimes underlying the behaviour of the E2 agent, both of which are required for the long-term interaction. For the C1 agent such a difference between dynamical regimens is not apparent. This potential difference between C1 and E2 analysed agents is further supported by the trajectories shown in Figure 8.5 in that a clear initial high and a final low oscillatory behaviour is observed for the E2 agent, while for the C1 one this behavioural differentiation is not clear.

For the C1 agent, the results in Figure 8.9 indicate that the controller requires a relatively long duration of the sensory stimulus (D) in relation to the gap between stimuli (W) in order to produce the necessary dynamics of interaction. In the opposite situation, namely with a relatively high W over D (e.g. (20; 54)), the agent's dynamics are more akin to those of the decoupled system when $I_i = 0$, which are far removed from the required dynamics of interaction. This evidence indicates that when the C1 agent 1 does not receive appropriate stimulation from the environment (or its partner), it will tend to remain around the $I_i = 0$ attractor.

In order to determine more precisely how sensitive the C1 and E2 controllers are to different input frequencies, we have investigated a systematic test across a range of sensory conditions. Figure 8.10 presents results testing the C1 and E2 neurocontrollers as a function of W and D in the

range [1, 200]. Dots in the plots stand for particular (D; W) combinations that resulted in the long-term dynamics of the agents converging in a pre-defined box of dynamical interest resembling the C zone in top rows of Figure 8.7 and Figure 8.8. This box represents whether the coupled *o2* and *o3* motor outputs reach a certain range [0.0, 0.2] and [0.8, 1.0], respectively, after 200 units of time. Under normal, coupled agent-environment condition, the motor nodes would generally be in this range.

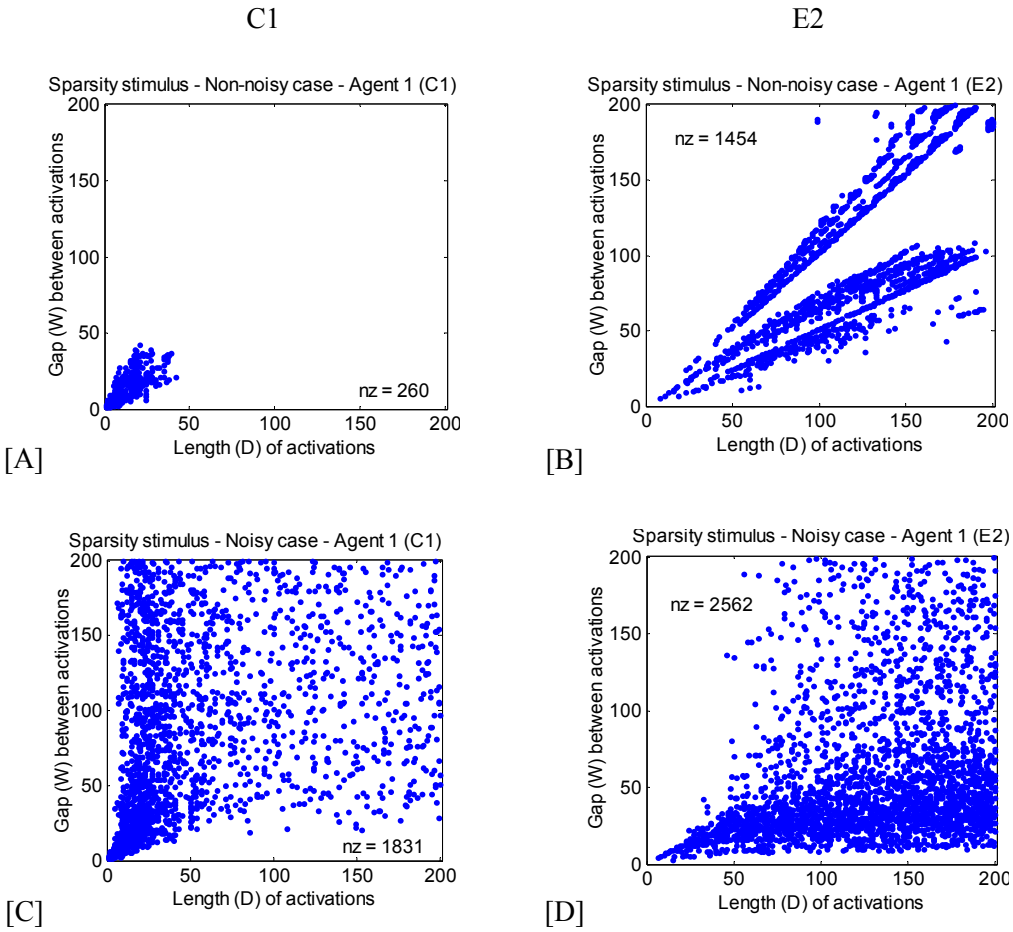


Figure 8.10 – Systematic study of the impact of stimulus duration (D) and the temporal gap (W) between activations. Dots represent values of D and W for which the output of motor nodes *o2* and *o3* ends up in the range of [0.0, 0.2] and [0.8, 1.0], respectively. These ranges are chosen to resemble the normal motor activities required to produce interactive behaviour. Each test lasts for 200 time steps. Plots [A] and [B] represent results without sensory switches, and [C] and [D] results with sensory switches (0.05 probability) for controllers C1 (*left column*) and E2 (*right column*). Labels 'nz' stands for the number of observations. Plots suggest that even the C1 controller makes some use of the random sensory switching in order to reach its operating regime. In addition, C1 controller is even more reliant for this test (rather than in the ongoing interaction) on the random sensory input than the E2 controller, as indicated by the comparatively small number of successful combinations shown in [A].

Figure 8.10-A shows the C1 experiments without sensory switches, indicating that the C1 controller reaches the target range of outputs only with 260 combinations of (D; W) values (D ∈ [1, 50]; W ∈ [1, 50]). Contrarily, Figure 8.10-B shows that the E2 controller reaches the dynamical box with 1654 combinations of (D; W). These results suggest that the E2 controller has an appropriate response to a wider range of sensory patterns in comparison to the C1 controller enabling long-term dynamics necessary for interactive behaviour as shown in Figure 8.8-*first row*. Interestingly, in further tests that include sensory switches (0.05 probability) under otherwise identical situations, we can observe that significantly more combinations of (D; W) induce the inner-systems to reach the target range of activation (1831 and 2562 cases for C1 and E2, respectively; cf. Figure 8.10-C&D). This strongly suggests that even the C1 controller makes some use of the random sensory switching in order to reach its operating regime. In fact, it seems that in some respects the C1 controller is even more reliant for this test (rather than in ongoing interaction) on the random sensory input than the E2 controller, as indicated by the comparatively small number of successful combinations shown in Figure 8.10-A.

However, this still leaves it unexplained as to why the E2 controller is more robust in general. It does have ca. 1.4 more combinations of (D; W) which would certainly help, and it might have something to do with the slightly different distribution of viable (D; W) combinations. Comparing to Figure 8.10-C and Figure 8.10-D, for instance, we can notice that the E2 controller is better at coping with longer durations of activation (D) when there is little gap between contacts (W). The C1 controller, on the other hand, appears to be generally better at dealing with short amounts of stimulation. How does this difference in sensitivity relate to the underlying dynamics?

8.3.6 Transient effects based on agent-environment interactions

Finally, we investigate here why it is that when the decoupled controllers are integrated into coupled agent-environment systems, their otherwise attractor-based dynamics are transformed into internal transient trajectories. Figure 8.11 shows plots representing the two-dimensional slices of the 4D phase portraits (3 nodes + sensor) for the two motor neurons of the C1 (*left*) and E2 (*right*) controllers. The *x*- and *y*-axes stand for the output of o_2 (leftward) and o_3 (rightward) motor neurons, respectively. The labels *sp0a*, *sp0b*, and *sp1* indicate the locations of stable points of the decoupled inner-systems when $I_i = 0$ and $I_i = 1$, respectively; *sn0* represents a saddle node for the $I_i = 0$ case for the E2 controller; *C* indicates an approximation of the region in which the coupled dynamics normally operate.

Note first that the engagement between two-embodied and situated agents can induce the controllers to remain far from their autonomous attractors. By analysing the dynamical flow that agents generate when their input switches between $I_i = 1$ and $I_i = 0$, we aim to get a better understanding of what produces these inner-transients dynamics. A high frequency change of sensory stimuli as we previously discussed will push the inner-system's dynamics toward a 'common' region (labelled as 'C' in Figure 8.11) along the flow of dynamical trajectories that

connect the autonomous attractors as if they co-existed in one state space. This effect happens despite that the initial dynamical state of the agents starts in the proximity of one of the autonomous attractors.

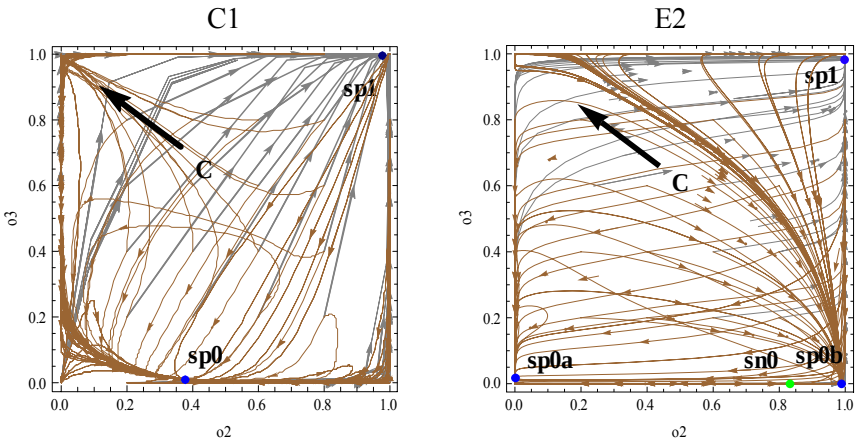


Figure 8.11 – Example of the hypothetical situation of dynamical flow with the transient state *C* that appear when inputs switches between I_i=0 and I_i=1. Axes represent motor neuron outputs (o_i) of the controller C1 (*left*) and E2 (*right*). See description in text for further details. Plots indicate the inner-system's dynamics region labelled as 'C' along the flow of dynamical trajectories that connect the autonomous attractors as if they co-existed in one state space.

We are now in a position to explain why the C1 agent cannot sustain the interaction with a non-interactive partner, because without the appropriate pattern of sensory stimuli the dynamics easily will fall in the *sp0* attractor (I_i = 0). This is because the *C* zone for the C1 agent's state space is highly connected through transient flows between *sp0* and *sp1* autonomous attractors (Figure 8.11-*left*). There will be a strong and quickly activated tendency to converge on *sp0* when agents are not in contact with each other and the agent is not able to receive appropriate stimulation. Contrarily, the flow of the simultaneous E2 autonomous attractors (Figure 8.11-*right*) show us in dynamical terms why this agent is initially slower than C1 agents to produce interaction behaviour (Figure 8.5-B). It turns out that the E2 controller's transient flows toward these attractors are neither directly nor highly connected with the *C* zone. In fact, these flows follow much longer transient trajectories toward *C*, which provides a certain amount of shielding against the effects of unexpected perturbation. In other words, the relatively reduced forms of connectivity between region *C* and the autonomous attractors of the E2 agent suggest why it does not discriminate between the responsive and non-responsive conditions. Essentially, it requires a much longer dynamical trajectory to reach *sp0a* or *sp0b* attractors in the initial stage of interaction, and after the preferred operating region *C* has been reached, the E2 agent no longer easily falls into the *sp0a* or *sp0b* attractors that do not provide the right conditions for interactive movements.

8.4 Discussion: the effect of perturbing functional conditions in behavioural robustness

In this chapter, we have conducted a preliminary investigation into the relationship between distributed mechanisms of cognitive behaviour and behavioural robustness in terms of a detailed dynamical analysis of two kinds of model agents. One of the lessons is that the benefit of having cognitive behaviour realized in a distributed manner depends on the specific role played by the environmental conditions. Some strategies of environmental distribution lead to more robust behaviour than others. In particular, if a brain-body-environment system *necessarily* depends on a set of specific environmental factors to sustain its behaviour, then it will be more vulnerable to environmental perturbations of this set than an inner-system for which several environmental factors are equally *sufficient* (see explanations for Figure 8.6). In other words, our results indicate that not all distribution is equal for robustness, and that an agent's dependence on a variety of sufficient conditions is more beneficial for its behavioural robustness than dependence on environmental factors that are necessary.

However, this is not to say that the role of the environment is diminished in the more robust system. On the contrary, these results support the idea that the amount of behavioural robustness cannot be deduced directly from properties of the controller by itself, but must be conceived in terms of the coupled brain-body-environment system. For instance, the analysed agents make use of context-dependent feedback to shape the different transients properties of their state space, and this reciprocal feedback loop is tightly integrated into the way they realize their behavioural strategies. What these results are point to is a potential range of different modes of cognitive integration, from strict task commitment to flexible behaviour. It would be of great interest to investigate possible dynamical mechanisms that would allow an embodied agent to adaptively regulate its own dependencies to switch between different modes of engagement (see also [Di Paolo & Iizuka, 2008]).

As we indicate in section 8.3.2, once more, we are here interested in behavioural robustness rather than on the ability of discrimination in agents. Whether behaviours are robust depends entirely on the behaviour that we want to study. Our analysis could be restated exactly opposite if we redefined our goal to be tracking only active agents (in the presence of sensorimotor perturbations), an in this case distribution is still 'better'. This issue is important to be acknowledged since it is a major point we are trying to make about distributed mechanisms for robust behaviour.

Finally, it is worth noting that the additional constraints placed on the CTRNN controller (section 8.2.3) made the evolution of agents that are more behaviourally robust against environmental perturbations easier. Future work could therefore investigate more closely the relationship between the role of local instability as indicated in section 8.2.3 and inner-transient dynamics in the generation of more flexible behavioural strategies. It would also be of interest to investigate the robustness of this type of controller against internal structural perturbations, in

comparison with standard CTRNN controllers. Finally, further investigations and theoretical discussions can concentrate on the relation between the dynamical and behavioural effects of the reported evolutionary constraints (section 8.2.3) and a similar (but poorly inspired) idea of how biological neurons remain far from attractors. For example, neurons can be maintained away from their fixed state by ion pumps and incoming signals from the rest of neurons in a network, generating necessary incoming stimuli for neural activity (e.g. neural spikes). This analogy can be associated to the frequency required for interaction in our model agent. Some of the consequences of the reported model have been addressed in this chapter, but the whole set of implications should be more fully investigated in future work based on this thesis.

8.5 Toward a metastable understanding of behavioural robustness

The experimental discussions given in this thesis consistently show that behaviours in our agent models associate with transient dynamics at neurocontroller level during coupling. These dynamics emerge from a distributed and functional organization that internal control uses to enable coherent and cognitive actions. We extensively discussed that at neurocontroller level the environmental coupled dynamics does not 'settle down' but showing an ongoing change marked only by transient interactive coordination, rather than being produced by a concrete dynamical structure at controller state space (e.g. a quasi-periodic dynamical trajectory or a limit circle in experiments in this chapter).

In other words, the dynamical attractors that emerge from agent-environment coupling vary (or move) in state space owing to activity-dependent changes of neurons and environmental modulations in the face of incoming sensing (see explanations around Figure 6.9 for an example of this point). Agents' simulated nervous systems operate in transient dynamics towards an (or several) attractor(s) that continuously moves, appears or disappears, in the phase space where the attractor landscape remains unchanged. In this respect, Varela *et al.* (2001) tell us that "the transient nature of associated to coherence behaviour is central to the entire idea of large-scale [neural] synchrony, as it underscores the fact that the system does not behave dynamically as having stable attractors, but rather metastable patterns." By metastable patterns, Varela *et al.* refer to a succession of self-limiting recurrent patterns (see [Kelso, 1995] and [Afraimovich *et al.*, 2008] for further explanations about metastability).

Clear examples of metastable dynamical patterns at internal control level are given for the one leg-walking agent (Chapter 7) and the two agents interaction task (Chapter 8). For instance, analyses of walking agents working with evolvable sensory offsets and sensory noise emphasize that motion dynamics work transiently among autonomous attractors. If the noise disappears during tests after evolution in these agents, neurocontrollers' dynamics would be 'trapped' among autonomous attractors, where two attractors alternate because of coupling but are fixed in phase space. Another example is the mobile-object tracking task detailed in Chapter 8, where 'C regions' representing metastable transient dynamics are generated because the nature of the interaction

model, rather than being produced by a concrete dynamical structure at controller state space (e.g. a quasi-periodic dynamical trajectory or a limit circle). Therefore, we can say that these agent models reach behavioural robustness by means of metastability at coupled dynamical level in whatever form the evolution of agents has come up with (e.g. cyclic dynamics resembling CPGs or RPGs as in Chapter 7, or common dynamical regions between autonomous attractors as in Chapter 8).

Although a common mechanism at controller (neural) level promoting behavioural robustness is still unknown for brain-based agents, we argue that the most plausible candidate for increasing behavioural robustness is 'dynamical integration rooted on internal-control, body and environment dynamics'. As shown in this thesis, this integration can be obtained via inducing distribution of behavioural mechanisms in systems that evolve, where such an integration constitutes the basis for several broader considerations about brain dynamics as coordinated spatio-temporal patterns (see [Kelso, 1995] and [Varela *et al.*, 2001] among other works). There are however different ways to induce such a distribution of behavioural mechanisms, which this thesis has discussed; that is, through:

(a) the use of external factors for behaviours, where environmental dependence is further developed by means of limited neurocontroller dynamics (Chapter 6);

(b) the exploit of feedback from the agents' body that is processed at neurocontroller level, where such a distribution is enlarged using sensory offsets and sensorimotor noise (Chapter 7);

(c) the development of different dynamical dependences for the two-agent engagement, where environmental dependence is further induced via relatively stable to noise, but sensitive to stimuli, internal (heteroclinic) dynamics (Chapter 8).

Under the vision promoted in this thesis (i.e. behavioural robustness is better understood in terms of distributed behavioural mechanisms), the internal nervous system of situated, embodied and dynamical agents appears as a resourceful complex system that satisfies simultaneously exogenous and endogenous constraints. These constraints arise by transiently settling in a globally consistent system state, where such a transient remains functional (robust) despite induced perturbations. By exogenous we mean constraints imposed from outside an internal control system (e.g. dynamical limitations imposed by agents bodies), in contrast to endogenous meaning constraints generated from within the system (e.g. the dynamics created by the topology of the network of neurons).

The relatively novel views on how 'brain'-based (minimal) agents reach robust behaviour by exploiting transient dynamics might throw light on the emergent principles that link neuron and network dynamics (and eventually mind), as the large-scale integration of internal control activity coupled with the environment (including body) during ongoing tasks.

Chapter 9

Concluding remarks

"No great discovery was ever made without a bold guess."

Isaac Newton

Many of the observations that we describe here are not completely new. Often they have existed previously in some form or another, but have not been presented together in a coherent fashion. The combined interpretation of pre-existing ideas with our experimental observations is reported in this final chapter, and we believe the contribution is a relatively novel and satisfying approach to systemic robustness. We hope that this thesis motivates the reader to see distributed functionality as emulating behaviourally robust systems instead of robustness being entirely determined 'from inside'.

9.1 Systemic robustness as a distributed property

As we have discussed in previous chapters, there is a growing trend in the cognitive and neurosciences fields to view cognitive behaviour as distributed across an extended, multi-level system. Our aim in this thesis is to present some theoretical and modelling work that investigates this outstanding issue. We have analysed formal dynamical agents placed in a variety of environments to address the hypothesis that behavioural robustness is better understood as a property grounded on dynamical relations among an agent's nervous system (brain), its body, and its environment. The ER technique is employed to synthesize embodied and situated agents with neurocontrollers as 'nervous systems'. These neurocontrollers produce dynamics that sustain different behavioural modes to accomplish our modelled tasks. Dynamical systems theory and statistical analyses are used to support conclusions given in this work.

Our lessons *complements* the common belief in literature that robustness is solely ensured by internal mechanisms (Figure 1.1-A). The coupled dynamics of the brain-body-environment system is also part of, and perhaps an essential component to, the agent's ability to generate environmental actions despite perturbations. However, the agents' internal control systems in our experiments do not have a priori mechanisms ensuring robustness, such as functional modularity and redundancy (see [Kitano, 2004a]). Evolution must instead find mechanisms to produce robust behaviours using coupled dynamics in given different experimental scenarios. The scope of experiments varied from situated (phototaxis and mobile object tracking task in Chapter 5 and Chapter 8, respectively), embodied (one-leg walking task, Chapter 7), to minimal cognitive agents (categorical perception task, Chapter 6). Perturbations in our experiments were both genetic (mutational variation) and non-genetic (e.g. environmental, sensorimotor, and structural perturbations). We succeeded in artificially evolving agents that show robustness in all of those situations.

Most experiments demonstrate a tendency toward robust traits in agents with more distribution of their behavioural mechanisms — those agents showing further dependence on conditions in 'nervous system', body, and environment. Experimental evidence in this thesis reinforces the idea that the distribution of behavioural mechanisms is a significant factor for further behavioural robustness. However, this thesis reports that diverse types and magnitudes of perturbations cause performance to differ given different mechanistic distributions, depending on whether perturbations affect the functional dependencies of control systems to body and environment dynamics and whether these dependencies are necessary or sufficient to sustain behaviours (see results in Chapter 8 and Chapter 6). To our knowledge, this observation has not been previously discussed in associated literature (see Chapter 2 for a survey).

The next sections contain a summary of the results from this thesis. Sections 9.2 and 9.3 discuss some contributions and implications of our work. These sections extend arguments supporting our conclusions that behavioural robustness spans both the dynamics of internal mechanisms and dynamical interactions of the whole system. In particular, section 9.2.1 summarizes the main lessons of this work and conclusions from experiments. Section 9.2.2 proposes some derived observations. Section 9.5 gives new research questions raised by the work in this thesis. Finally, section 9.6 presents some closing comments.

9.2 Contributions

Using ER techniques, we have studied the emergence of behavioural robustness across a broad class of dynamical systems and a variety of perturbations (e.g. mutational and sensorimotor). Our experimental motivations are based on the fact that works in ER have so far paid relatively little attention to distributed cognition [Ziemke *et al.*, 2004] and behavioural robustness [Silverman & Ikegami, 2010] in environmentally coupled agents. In particular, our work addresses current discussions on cognitive distribution as central to the emergence of cognitive processes and robust

behaviours in ER (see [Fernandez-Leon, 2011][Fernandez-Leon & Froese, 2010] for recent examples).

The promoted holistic view of behavioural robustness however raises difficulties for future experimental studies: the dynamical mechanisms that produce robustness *cannot be studied* as isolated parts in most biological systems. Taking the dynamics of the environment (including body) into account generally makes the study of robustness a hard problem, even more difficult. Because of this, we have concentrated on minimal models and analyse dynamically contributions of systemic components (agent-environment) to robust and adaptive behaviour.

The general observations proposed in this thesis are listed as follows. Behavioural robustness as a dynamical process emerges from the coupled brain-body-environment system, rather than from isolated mechanisms inside the brain (or in our case neurocontrollers). Not all dynamical strategies or behavioural mechanisms are equally robust to certain perturbations; much certainly depends on the effects of the perturbation on an agent's functional dependencies (typically sensory information, but not exclusively). Functional dependencies, as prerequisites for particular behavioural mechanisms, emerge from the exploitation of environmental opportunities developed during the ER evolutionary stage. Next sections give further details of these observations.

9.2.1 Main lessons from experimental chapters

The following descriptions summarize the main observations of the experimental chapters (see also section 1.4 and section 2.5 for other remarks).

Not all distribution of agents' cognitive mechanisms are equally helpful in ensuring behavioural robustness.

Experiments in Chapter 8 showed us that analysed agents (one dynamically restricted and other non-restricted, section 8.2.5) presented behavioural mechanisms distributed differently among the brain-body-environment. Both agents require sensory signals to sustain interaction behaviour despite sensorimotor perturbations. However, the dynamically restricted agent exhibits less dependence to responsive partners in comparison to a non-restricted agent.

In the presence of sensorimotor and environmental perturbations affecting brain-body-environment interdependencies, a wider distribution (further systemic dependencies) of the behavioural mechanisms seems to be beneficial for robust behaviour. This is observed only if *not all* of the necessary conditions to produce behaviours are affected by significant levels of perturbation. We have analysed a non-restricted agent in Chapter 8 that necessitates the presence of a responsive partner to produce interaction, but does not require other factors to sustain interactive behaviour (e.g. sensory or motor noise). Importantly, we conclude that it is *not* the wider distribution, as such, which is beneficial for behavioural robustness, it is the

particular kind of distribution — a collection of individually sufficient conditions (rather than necessary ones) — that produces agent's vulnerability to sensory perturbations.

The observation of particular types of environmental dependencies also applies to the monostable agent analysed in Chapter 6. The agent shows a necessary dependence on objects in the environment to produce categorical perception behaviour. The requirement of an object in the environment is enforced conceptually: monostable agents cannot produce the necessary internal dynamics without the continuous stimuli from objects in the environment. This stimulus enables monostable agents to work far from their unique autonomous attractor to produce controls to catch or avoid falling objects. The comparison to bistable agents has showed us that monostable agents are slightly but significantly more robust to a wide set of sensorimotor, morphological, and mutational perturbations. This is mainly because perturbations can affect the 'internal state' that bistable agent's neurocontrollers are evolved to maintain after sensing the environment. Chapter 6 finally discuss that the maintenance of an internal state produces more behavioural autonomy in relation to the environmental state in bistable agents than in the monostable case, which is not certainly beneficial for behavioural robustness in analysed cases. An example of such autonomy is the maintenance of agent's movements when the agent is not currently sensing an object.

The relative increase in internal complexity of small agents has both virtues and disadvantages for exhibiting coherent behaviours under perturbations.

A long these same lines, the autonomy that encompasses behaviours in bistable agents — those actions that do not require the continuous presence/absence of certain object in the environment— manifests as ultimately 'wrong decisions' when the state of the agent is affected by perturbations. Analysed mono- and bistable agents in Chapter 6 both respond to cues from the environment, but when the internal state of bistable agents is perturbed their relative dynamical richness (i.e. having more internal attractors) is not necessarily an advantage in producing the 'right behaviour'. When perturbations are big enough to produce a change in the agent-internal's state, the bistable agent can shows approaching rather than avoiding behaviour in the presence of avoiding objects. This indicates behaviour being affected by the effects of perturbations on dynamical trajectories in the analysed bistable agent's internal milieu. When perturbations are small enough, both reported agents maintain their current states by 'tolerating' perturbations. The important lesson from those results is that systemic robustness can be also manifested as requiring a *robust transition* to an appropriate (internal) steady state in order to exhibit coherent behaviours.

The tuning of sensory mechanisms based on agent-environment interactions is not always beneficial for behavioural robustness, which depends on the complexity of incoming signals.

In Chapter 7, we demonstrate that the fine-tuning of sensory mechanisms through the evolution of sensory offsets has some negative and positive influence on agent's behavioural robustness: it depends on the complexity of incoming signals that agents should process and the effects of perturbations on internal dynamics. When evolving with multiple sensory offsets, we observe that agents perform a relatively more robust one-leg walking behaviour with noisy signals than agents evolved with one or zero sensory offsets. For example, results demonstrate that the use of a simple (one) sensory offset creates internal dynamical control in agents that necessarily depend on sensory feedback from a leg's angle in noiseless environments. In turn, perturbations in sensory feedback generate a considerable decay in performance. Robust behaviour also emerges after inducing a relatively low degree of mutational perturbations in medium or highly noisy environments.

The lesson from experiments in Chapter 7 is that agents show robustness by using the experience of interacting with the environment to tune their sensory mechanisms, but the level depends on the effects of perturbations on the feedback from agent's leg. Agents' sensory capacities of self-tuning their body senses are thus not always beneficial for sustaining one-leg walking behaviour, because the effect of sensorimotor perturbations on these dependencies. The importance of results in Chapter 7 is that such a demonstration, because of the simplicity, lays the foundation for further work on agent environmental dependency to exhibit behaviours.

From an evolutionary perspective, neural noise seems to bias selection toward neural systems that are resistant to the effects of bifurcations during internal transient dynamics.

In experiments described in Chapter 5, the analysed agents have dynamic landscapes that remain functionally the same during coupled dynamics (phototaxis behaviour) in the presence of sensorimotor and structural perturbations. Robust behaviours arise in agents as a combination of locating the neurocontroller's dynamics in regions of parameter space where bifurcations produced by neural noise are unlikely to occur and where, if bifurcations occurred, they remain in functional balance. Our findings suggest that robustness to perturbations in the face of neural noise may be a by-product of locating such regions of parameter space. In presence of certain systematic variations of parameters, the evolutionary process guarantees behavioural robustness to these variations, but it cannot ensure robustness to variations that were not given during evolution.

In Chapter 5, we also discuss that the evolution of agents under certain levels of neural noise produces robustness to this condition. Under the right parameter definition, every tested agent evolved in a minimal scenario, and in the presence of certain level of additive neural noise has

the capacity to succeed at goal approaching. Evolutionarily emerged robustness is a necessary property of agents if they are to overcome the failings of induced neural noise and perturbations during lifetime (which agrees with Jakobi's (1998a) seminal work in ER on behavioural robustness). Our last observation confirms Jakobi's proposal in how to induce the emergence of behavioural robustness in artificial agents. Results indicate that noise 'forces' evolution to this type of robustness in whatever form evolution cares to come up with. However, when agents evolved with certain level of neural noise are evaluated with higher levels of it during tests after evolution, agents show a decay in performance (Chapter 5). If the level of neural noise was lower during evolution, agents instead exhibit at least similar fitness than after evolution.

9.2.2 Further observations from experimental results

An integral observation from the discussions in this chapter is that robust behaviour emerges because of continuous interaction between the neurocontroller, the body, and the environment under certain types and levels of perturbations given thorough evolution. Consequently, credit cannot be assigned for robust behaviour to any one isolated part of the coupled system. In particular, our experimental observations lead us to suggest a dynamical systems perspective on robust but adaptive behaviour that does not rely solely on attractors, but takes into account transient coupled dynamics as well[3]. There are several important implications of this broader, systemic view of behaviour robustness. The following comments are some consequences from the observations given in this section.

Unexpected behavioural features can emerge from an agent-environment coupled system.

In Chapter 8, two agents produce mobile-tracking behaviour despite sensorimotor perturbations, where agent interactions depend both on agents' own internal dynamics and the changing walking behaviour of the other agent. Each agent does not support interactive behaviour by itself without some level of stimuli from another agent (e.g. the presence of a responsive or a non-responsive agent). The emergence of internal dynamics working in transient in robust agents, and the relative independence to a responsive partner for producing interactive behaviour, were not expected before experimentation.

Internal-control dynamical strategies seem to be particularly useful for behavioural robustness in a task requiring repetitive behaviour in noiseless environments.

Experiments in Chapter 7 indicate that an agent directly sensing its environment (when no sensory offsets are available) emerges with an 'internal' dynamical mechanism that can help to sustain

[3] General idea based on personal communications with Dr. Takashi Ikegami in 2007 and 2008.

behaviours despite reductions in the agent's sensing capacity. In noiseless environments, such dynamics emerge in one-legged agents using local bifurcation in which a fixed point of the analysed neurocontroller's dynamics loses stability and a small amplitude limit cycle emerges from a fixed-point attractor (i.e. a Hopf bifurcation [Strogatz, 1994]). This is evidence therefore that evolution can generate controllers with an internal dynamical strategy that agents use to sustain behaviours during coupling. Our observations and those given in section 9.2.1, again, reinforce the idea that behavioural robustness cannot be deduced directly from the properties of the controller alone (inside agents); it mainly arises from emergent behavioural properties of the coupled brain-body-environment system as a whole.

9.3 Have we obtained biologically plausible robustness?

The experimental models presented in this thesis are far from emulating realistic examples of biological robustness. However, they provide theoretical evidence toward particular kinds of robust behaviours that may exist in the biological world (e.g. categorical perception, goal seeking, and walking behaviours). The key assumption is that biological organisms have evolved in coupled, controller-body-environment conditions. Simulated models of biological mechanisms with this coupling allow systematic tests that are *not* currently amenable to experimental techniques. The methods proposed in this thesis are taken as a starting point to develop such work.

Even in minimal cases, it is not trivial to evaluate the robustness of coupled systems, at least in an absolute sense. However, we can always ask: '*robustness as compared to what?*' and '*how does it emerge?*' in order to investigate the idea of robustness in any particular context. From an experimental viewpoint, a more interesting formulation of the study of robustness is: 'Is there a common dynamical mechanism producing behavioural robustness in a set of related bio-inspired models?' A universal mechanism is difficult to conceive fully-formed[4]. Unfortunately, heuristic answers to these questions are not enough because discussions around systems dynamics require no less than analysis of mathematical models. For this reason, we base this thesis on concrete experimental scenarios proposing comparisons that relate to each other. We suspect that additional theoretical directions will come from studies of behavioural robustness in connected, but different domains.

9.4 Lifetime robustness, but evolutionarily constrained

We have based this thesis mostly on a minimal evolutionary technique (ER), and our systematic analyses of the emerged mechanisms approximate many dynamical aspects of relatively simple living forms (e.g. adaptation and habituation processes [Ashby, 1958a, 1960]). Adaptation via evolution is observed in the dynamical analysis of behaviours in our models, where the concept of

[4] Conclusion based on a personal communication with Dr. Randall Beer in 05/2010 (see also [Beer, 2005]).

habituation to perturbations is also reflected in our definition of robustness in section 2.4 (in the face of an historical process). This thesis has defined robustness as a historical systemic property (agent-environment) that enables functionality in the presence of internal and external perturbations. Again, the introduced definition implies discussions on systemic robustness in (*i*) a system with a history of interactions with the environment, (*ii*) perturbations throughout the history of an agent-environment system, and (*ii*) a (internal) systemic function (or a set of them) that should 'actively' be maintained (by tolerance or adaptivity [Di Paolo, 2005]; see also [Carlson & Doyle, 2000, 2002]). Our definition covers a wide range of perturbations during an agent's lifetime (e.g. internal, environmental, and mutational), a range of systems (e.g. embodied, situated, and minimally cognitive), and a set of systemic functions (e.g. sensory and motor capacities).

All behaviours emerging in models for this thesis come from an evolutionary process. Those agents showing better performance during evolution will continue and create other agents inheriting similar behavioural mechanisms with robust properties. An example of this process is given in Chapter 5, where robustness to neural noise emerges in agents after their evolution. In contrast, changes in the features of the organism due to adaptation during its lifetime cannot propagate back into the genes. The relationship between evolution and robustness, however, requires further investigation mainly because this thesis *does not* propose studies on the development of agents.

Robust behaviour can (sometimes) increase evolutionary fitness, especially if the selection method implies lots of uncertainty and noise like in Jakobi's (1998a, 1998b) experiments. However, this does *not always* mean that the explanation of robustness is evolutionary. This is in account to a common question: "What historical process produced this robust behaviour?" Nevertheless, one can answer instead: "Why is the system robust in this way and to these perturbations and not others?" The behavioural mechanisms arise in our models both evolutionarily and dynamically during lifetime. We can ask consequently, what is required for robust and adaptive behaviours after evolution in our experiments?

Ashby (1960, p. 223) has proposed that the existence of genetic-defined, inborn regulatory mechanisms in animal nervous systems can demonstrate adaptive and robust behaviours during lifetime, which can guide further discussions as follows. Genetically defined behavioural mechanisms can involve indirect means to adapt to or tolerate unforeseeable perturbations. For example, general mechanisms like structural (synaptic) plasticity in the brain can provide adaptation and learning during an organism's lifetime after morphological perturbations [Di Paolo, 2000, 2003]. Through interactions with the environment, the organism fine-tunes its gene-based mechanisms to exhibit precise behaviours. What Ashby have suggested is that gene-patterns allow the organism to form its own behavioural adaptation, guided in detail by the environment (see 'ancillary regulation' in [Ashby, 1960]). In this respect, experiments described in Chapter 7 exemplify sensory (body signals) regulations that agents use to exhibit behaviours.

Whether genetically defined mechanisms can indirectly produce behavioural robustness in biological organisms is hard to support using the evidence given in this thesis. This is because our

interest is on robustness during organism lifetime rather than studying the emergence of mechanisms during evolution supporting behavioural robustness. However, as we previously discussed, we observe that simple mechanisms in our experiments come from indirect genetic regulation in the face of functional dependencies to brain, body, and environment. Any explanation of these behavioural mechanisms is in any case certainly *incomplete* if we do not focus on associated brain-body-environment dynamics.

9.5 Future work

The work presented in this thesis has aimed to understand robustness using a systemic and algorithmic perspective. This goal is ambitious in a bio-inspired research field without a widely accepted theory of biological robustness. Kitano (2007) has recently proposed a preliminary version of such a theory, based on studies of some biological systems with complex dynamics (e.g. immune and cancer systems [Kitano, 2004b, 2006]). The focus of Kitano's work is in the identification of mechanisms ensuring robustness (e.g. modularity, redundancy, decoupling, among others) that facilitate evolution and where evolution favours robust traits.

The most obvious next step of this thesis is to study robustness in complex adaptive systems (see [Ahmed *et al.*, 2005]). In this context, the production of robust behaviours will not only be generated as actions after sensing external cues, but can be the result of internal self-organized processes that are used by an organism to regulate or adjust a high-level environmental coupling (rooted on internal or 'self-imposed' restrictions). In fact, the conceptual difference of adaptive biological organisms and the agents implemented in this thesis is in that the former type is governed by self-organized dynamics during agent lifetime, while the latter type emerges from an evolutionary process (as we have discussed in section 9.4). Despite that cells are far from being simple systems (see protocells as an example [Mavellini *et al.*, 2008][Munteanu & Solé, 2006][Solé *et al.*, 2007]), an possible line of research might focus on the effect of perturbations on cell-like systems, and how they remains functional after internal malfunction and external perturbations (see [Kaneko, 2006]).

Another future direction might also be to study how cell-like systems can lose cognitive capacity and associated functionality under perturbations (see [Beer, 2004a, 2004b] for examples). In fact, the connection between minimalist cognitive science and biologically inspired models with robust properties is largely unexplored. The study of internally regulated agents in particular could be an interesting next step, where the environment does not determine but affects future actions. Our intuition is that in biological systems the connection to the environment varies over time (as a distributed process) and allows the agent-environment interface be modified by the organism itself (see [Di Paolo & Iizuka, 2008]). Agents could be studied with internal requirements like homeostasis, allostasis, or avoiding 'death' based on 'their metabolic definitions', which drives changes in the agent-environment interface. Through these requirements, agents may potentially emerge with dynamics being affected by internal norms (e.g.

homeostatic requirements [Di Paolo, 2002a, 2002b]), and exhibiting robust and adaptive behaviours as well. The evolution of these agents by means of Darwinian selection is also a feasible continuation of this thesis.

The work proposed by Furusawa and Kaneko (1998, 2001) is a tentative research direction based on the 'chaos hypothesis' in stem cell systems. Stem cells are defined as cells that are capable of proliferation, self-maintenance of their population, production of differentiated cells, and regeneration of the tissue in concern [Potten & Loeffer, 1990]. Furusawa's and Kaneko's observations suggest that the behaviour of these 'undifferentiated cells' can change flexibly according to environmental cues, while 'differentiated cells' have no such flexibility. This idea points out that stem cells can respond to environmental changes adaptively *without* pre-programmed internal mechanisms, but based on external regulations (e.g. cell-cell regulations that keep internal dynamics stable with respect to changes in environmental factors). Their observations agree with our discussion of distributed mechanisms for behavioural robustness and therefore warrant further investigation.

9.6 Final remarks

Experimental evidence and theoretical discussions in this thesis demonstrate the importance of understanding behavioural robustness as a dynamical and systemic process. This work supports the idea that robustness cannot be understood solely from mechanisms in an agent's internal milieu. We show that the evolution of minimal models produce agents that can perform robust traits in different scenarios without explicit internal mechanisms ensuring behavioural robustness.

The prime motivation for this thesis can be expressed as a search for the simplest interpretation of what affects to systemic robustness in terms of an interface between the internal and external world of organisms. Aside from the practicality of finding such an interface in biological organisms, by understanding emergent dynamics at an organism-to-environment systemic level, this thesis serves as a baseline from which to understand the causally connected interplay between structure and behaviour in organisms. We demonstrate clearly that such a dynamical interface is possible, as distributed processes in a brain-body-environment coupled system. Nevertheless, after this experience it seems likely that even more elegant and useful interpretations can be developed with further work. The theoretical perspective on systemic robustness provided in this thesis can effectively guide the understanding of robust phenomena in the real realm (where the holistic study is often impractical). The work in this thesis is a small contribution toward that ambitious goal, through the creation of a theoretical and algorithmic bridge between dynamics and robustness at coupled system level.

Appendixes

This appendix gives some details of the neurocontrollers and the analyses described in this thesis, and contains only some details and basic descriptions. Full justification and explanations can be found in each experimental chapter.

A.1. Chapter 5: structural description of studied neurocontrollers

Table A.1 shows the parameters of NC#9 and NC#3 neurocontrollers analysed in Chapter 5.

parameter	NC#9	NC#3
w (2;4)	-5.879421	0.4761854
w (3;4)	7.96813	0.0074078
w (3;5)	-5.82751	-7.969773
w (2;5)	-5.71487	4.795505
w (4;5)	-2.07358	2.631955
w (5;4)	-4.4690	4.28801
w (5;1)	2.59092	8.511997
w (5;0)	-6.18280	0.4603699
w (4;1)	-8.592732	-0.815977
w (4;0)	-3.745095	-2.467590
w (0;1)	9.806875	-4.513274
w (1;0)	-8.25163	6.378496
w (1;1)	7.62216	-3.69554
w (0;0)	6.838076	-1.31772
τ (0)	8.11	5.27
τ (1)	5.18	1.19
τ (4)	0.53	4.28
τ (5)	1.36	7.43

Table A.1. Parameter values for the analysed NC#9 and NC#3 controllers in Chapter 5. Parameters are neuron time constant (τ) for interneurons (neurons 4 and 5) and motor neurons (neurons 0 and 1), and *w(j;i)* is the strength of the connection from the *j*-th to the *i*-th neuron (where neurons 2 and 3 represent sensors).

A.2. Chapter 6: structural description of studied neurocontrollers

This section presents a brief description with some structural details of the analysed mono- and bistable neurocontrollers studied in Chapter 6.

	τ	θ	g
input nodes	1	-5.113288	3.4534759
interneurons	1.3999523	-3.65526	1.46661995
	1.6748580	-1.8287704	-2.97110
	1.491153	1.23616067	-3.47452020
motor neurons	1.177145	-1.88478603	0.84192602

Table A.2. Parameter values for the analysed bistable controller in Chapter 6. Parameters are neuron time constant (τ), bias term (θ), and gain (g) for sensors, interneurons and motor neurons.

	τ	θ	g
input nodes	1	-3.05446216	1.2003586
interneurons	1.2522383	-4.908101	-0.6872947
	1.44578375	2.248604	3.245322
	1.93729866	4.6994562	-0.442940216
motor neurons	1.89983936	-1.28420002	-0.8616882

Table A.3. Parameter values for the analysed monostable controller in Chapter 6. Parameters are neuron time constant (τ), bias term (θ), and gain (g) for sensors, interneurons and motor neurons.

The sensory inputs for the analysed mono- and bistable controllers respectively inhibit 50% and 30% of internodes. Sensory gains are 18.77% higher and the output motor gain is 19.66% higher for the bistable controller. Inhibitory self-connections in the hidden layer are the same in both controllers (33.3%). The magnitude of excitatory self-connections for the bistable controller in relation to its mean is 10.67% higher than for the monostable controller, and 47.82% higher for inhibitory self-connection in the monostable case. For the rest of synapses (i.e. hidden-hidden and hidden-output connections), the proportion of inhibitory relations are 40% for mono- and 46.67% for the bistable cases, in this order. Descriptions of neurocontrollers in Table A.2 and Table A.3 use to $\tau(i)$ as the i-th neuron time constant, $\theta(i)$ as a bias term, and $g(i)$ is a gain. The multiplicative output factors for the bistable and monostable case are 9.411341 and 7.8651156, respectively. Synaptic connections for both neurocontrollers are given in Table A.4 where $w(j;i)$ is the strength of the connection from the j-th to the i-th neuron.

Synaptic connection		Synaptic strength (weight)	
		Bistable controller	**Monostable controller**
w (7;8)	*w* (6,11)	-1.1350246	-2.8306862
w (0;8)	*w* (6,10)	0.4590694	1.816273920
w (0;9)	*w* (6,9)	2.75194655	-1.487287632
w (0;10)	*w* (6;8)	1.99533618	-1.49479370
w (0;11)	*w* (6;7)	2.22800900	-0.03968038
w (1;7)	*w* (5;11)	2.67058211	2.93358006
w (1;8)	*w* (5;10)	4.03330822	0.31438768
w (1;9)	*w* (5;9)	-3.471269970	4.87091577
w (1;10)	*w* (5;8)	1.81638780	3.06964367
w (1;11)	*w* (5;7)	0.583812639	0.845049525
w (2;7)	*w*(4;11)	-3.37899945	-2.48139349
w (2;8)	*w* (4;10)	-0.2549976	4.59213775
w (2;9)	*w* (4;9)	1.03743165	1.3362475
w (2;10)	*w* (4;8)	-1.1628953	-3.1542865
w (2;11)	*w* (4;7)	4.0419153	-3.33080908
w (3;7)	*w* (3;11)	0.41824655	-3.2530546
w (3;8)	*w* (3;10)	-0.30582314	-2.7786978638
w (3;9)		2.31644254	1.273289142
w (7;7)	*w* (11;11)	3.8598409	2.097115279
w (7;8)	*w* (11;10)	-3.5211957	1.4062679493
w (7;9)	*w* (11;9)	2.3674840	-4.97434786
w (7;10)	*w* (11;8)	3.70729360	0.446909383
w (7;11)	*w* (11;7)	1.7403904	4.78665459
w (8;7)	*w* (10;11)	4.7659135	2.138113079
w (8;8)	*w* (10;10)	-1.3299419	-2.78104572
w (8;9)	*w* (10;9)	3.2041375	-2.27983025
w (8;10)	*w* (10;8)	-0.0049854	1.509471188
w (8;11)	*w* (10;7)	-2.6927443	3.193746067
w (9;7)	*w* (9;11)	-0.2792409	1.28254231
w (9;8)	*w* (9;10)	-4.877590	-0.59442662
w (9;9)		4.0590038	3.06616899
w (7;12)	*w* (11;13)	-0.4683591	1.309800199
w (7;13)	*w* (11;12)	3.5020927	-0.6958523
w (8;12)	*w* (10;13)	1.6299242	-3.45325280
w (8;13)	*w* (10;12)	0.32376588	3.20156433
w (9;12)	*w* (9;13)	-2.035150892	-3.38806928

Table A.4. The synaptic connection strengths of the analysed neurocontrollers in Chapter 6. *w(j;i)* is the strength of the connection from the *j*-th to the *i*-th neuron.

A.3. Chapter 6: statistical comparison between sets of agents

This appendix describes a brief analysis that supports the experimental comparisons between sets of mono- and bistable agents given in this chapter. This analysis illustrates the similarity of fitness distributions obtained with both sets that are generated with slightly different fitness functions as specified in sections 6.3.3 and 6.3.4 using (a=1/3; b=10) and (a=2; b=4) parameter values. The following descriptions only contain some of the main details and results of this validation. See please [Minium *et al.*, 1998] to extend the discussions about related statistical method proof.

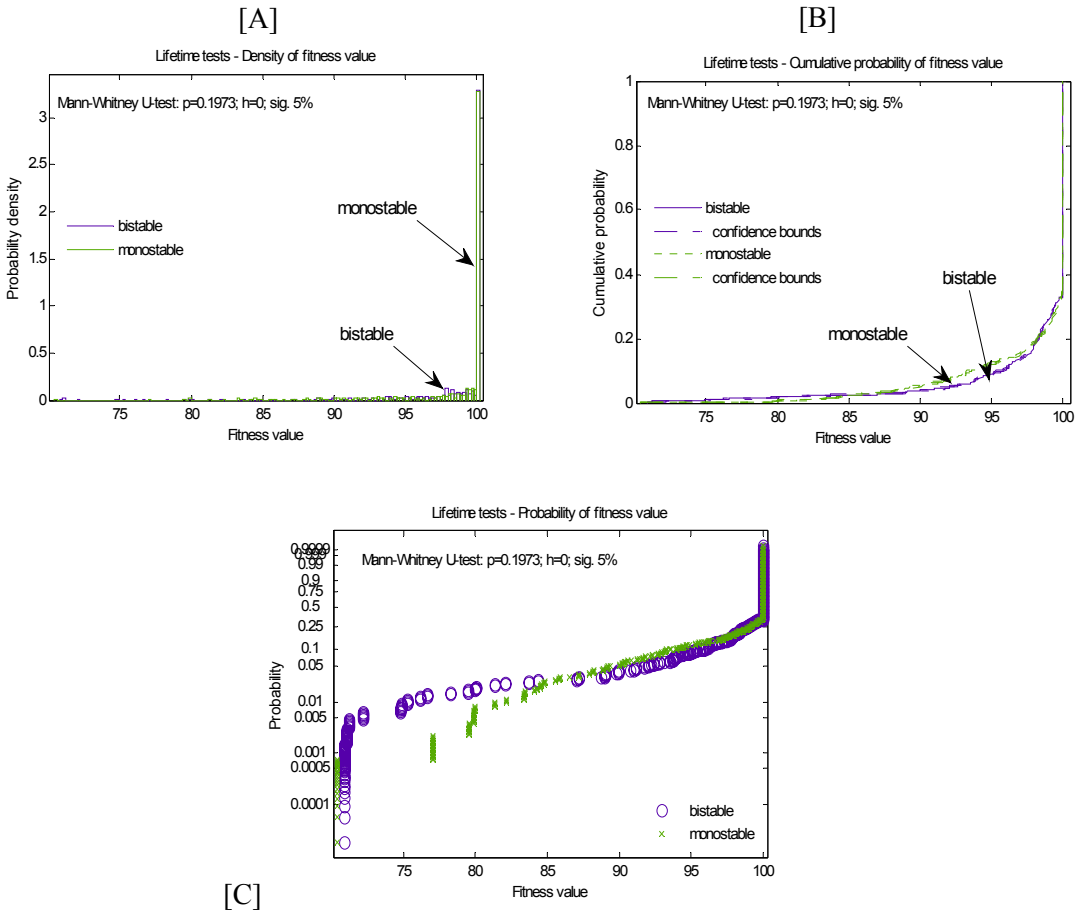


Figure A.1 – Different statistical comparisons between the mono- and bistable sets of agents. Plots describe the [A] density of probability of fitness value, [B] probability of cumulative fitness value, and [C] the probability of fitness value for each set (20 neurocontrollers each). The Mann–Whitney U-test suggests that we can compare the two (mono- and bistable) fitness distributions with equal medians at 5% significance level (95% confidence level) based on our parametrical settings. Imprints in each plot indicate the significance level (p) and the acceptance of the null hypothesis (h=0), namely that we cannot reject that both sets are equally distributed (sig. 5%).

Figure A.1 indicates that the lifetime fitness of mono- and bistable sets of agents are made on identical distributions with equal medians. These fitness distributions are obtained for the experimental configuration given in section 6.3.5 during lifetime tests (tests after evolution). The statistical analysis in Figure A.1 is made against the alternative that fitness distributions do not have equal medians. The analysis indicates that both sets of agents follow a 'Generalized Pareto' distribution. Since the distribution of fitness, the use of *t*-test to tell if there is a significant difference between samples is not appropriate.

After applying a non-parametric significance tests on the fitness distributions obtained with the two sets of agents, the Mann–Whitney U-test [Mann & Whitney, 1947] (also known as Wilcoxon rank sum test [Gibbons, 1985][Hollander & Wolfe, 1999]) suggests that we can compare both distributions with equal medians at 5% significance level (95% confidence level). The applied Mann–Whitney U-test consequently demonstrates statistically that both sets of 20 best-fit mono- and bistable agents produce similar distributions of fitness with (a=1/3; b=10) and (a=2; b=4) values, which enable us to compare both sets of agents.

A.4. Chapter 7: structural description of studied neurocontrollers

This section briefly describes the selected neurocontrollers in Chapter 7 with some structural detail. The number of inhibitory synaptic connections for CUE0(N), CUE1(N) and CUE3(N) are 44%, 40% and 68%, where 60%, 60% and 100% of the self-connections are also inhibitory, respectively. The time constant average is 6.2848 (std: 4.0816), 3.2555 (std: 2.8635) and 5.1455 (std: 3.8290), and the average of biases is -0.9872 (std: 8.2211), 2.2717 (std: 6.4479) and -3.8639 (std: 9.7061), in that order. The sensory offset for the single valued CUE1(N) is -0.183700, and for the multi valued CUE3(N) is 0.332600 (neuron 1), 0.477600 (neuron 2), and 0.523600 (neuron 3). The given percentages indicate that there are no significant differences in the structure of CUE0(N) and CUE1(N) controllers in terms of inhibitory connections, but CUE3(N) has a relatively high number. This may allow CUE3(N) to behave more in a stable way than the other controllers (see Chapter 7). Table A.5 shows the parameters of the studied controllers.

Studied neurocontrollers					
CUE0(N)		**CUE1(N)**		**CUE3(N)**	
w (1;1)	4.115200	w (1;1)	20.000000	w (1;1)	-0.644000
w (2;1)	15.342900	w (2;1)	20.000000	w (2;1)	15.389800
w (3;1)	4.670600	w (3;1)	14.581900	w (3;1)	5.811400
w (4;1)	19.029200	w (4;1)	-16.257300	w (4;1)	-19.727600
w (5;1)	-20.000000	w (5;1)	-1.939400	w (5;1)	-0.869200
w (1;2)	20.000000	w (1;2)	20.000000	w (1;2)	20.000000
w (2;2)	-3.724600	w (2;2)	-8.445500	w (2;2)	-4.660300
w (3;2)	4.254400	w (3;2)	6.440300	w (3;2)	1.821400
w (4;2)	2.813800	w (4;2)	10.286000	w (4;2)	14.194300
w (5;2)	-0.907400	w (5;2)	-20.000000	w (5;2)	14.188000
w (1;3)	-14.189600	w (1;3)	-20.000000	w (1;3)	-20.000000
w (2;3)	-20.000000	w (2;3)	-15.517900	w (2;3)	-20.000000
w (3;3)	-15.695500	w (3;3)	-2.950900	w (3;3)	-3.080200
w (4;3)	-1.381300	w (4;3)	10.833400	w (4;3)	17.713500
w (5;3)	20.000000	w (5;3)	-1.449000	w (5;3)	-14.707000
w (1;4)	16.558700	w (1;4)	18.312300	w (1;4)	-20.000000
w (2;4)	11.729000	w (2;4)	9.960900	w (2;4)	-20.000000
w (3;4)	-12.379200	w (3;4)	13.938500	w (3;4)	0.402800
w (4;4)	-19.800400	w (4;4)	0.845100	w (4;4)	-15.837400
w (5;4)	-16.181700	w (5;4)	0.353500	w (5;4)	-9.345400
w (1;5)	0.386200	w (1;5)	20.000000	w (1;5)	-13.955800
w (2;5)	2.180100	w (2;5)	-8.105300	w (2;5)	-18.368600
w (3;5)	-20.000000	w (3;5)	-8.370500	w (3;5)	-6.073300
w (4;5)	1.282000	w (4;5)	5.430000	w (4;5)	-20.000000
w (5;5)	9.696400	w (5;5)	10.556800	w (5;5)	-8.818400
θ (1)	0.888800	θ (1)	-4.194600	θ (1)	-5.512600
θ (2)	-5.338900	θ (2)	4.674300	θ (2)	-8.606000
θ (3)	12.101300	θ (3)	5.441400	θ (3)	15.000000
θ (4)	-9.476600	θ (4)	-4.638900	θ (4)	-7.216800
θ (5)	-3.110400	θ (5)	10.076300	θ (5)	-4.165900
g (1)	1.000000	g (1)	1.000000	g (1)	1.000000
g (2)	1.000000	g (2)	1.000000	g (2)	1.000000
g (3)	1.000000	g (3)	1.000000	g (3)	1.000000
g (4)	1.000000	g (4)	1.000000	g (4)	1.000000
g (5)	1.000000	g (5)	1.000000	g (5)	1.000000
τ (1)	9.917800	τ (1)	2.023500	τ (1)	9.517500
τ (2)	0.185900	τ (2)	4.185700	τ (2)	1.938600
τ (3)	4.749300	τ (3)	0.370100	τ (3)	0.422100
τ (4)	6.571000	τ (4)	1.932700	τ (4)	7.474400
τ (5)	10.000000	τ (5)	7.765600	τ (5)	6.374700
		CUE (1)	-0.183700	CUE (1)	0.332600
				CUE (2)	0.477600
				CUE (3)	0.523600

Table A.5. Parameter values of the analysed neurocontrollers in Chapter 7. Where $\tau(i)$ is the i-th neuron time constant, $w(j;i)$ is the strength of the connection from the j-th to the i-th neuron, $\theta(i)$ is a bias term, and $g(i)$ is a gain; CUE (i) represents the sensory offset of the i-the neuron.

A.5. Chapter 8: structural description of studied neurocontrollers

This section briefly describes the structure of the C1 (non-structurally restricted) and E2 (structurally restricted) neurocontrollers that we have studied in Chapter 8 (see Table A.6). The number of inhibitory synaptic connections for C1 and E2 are 44.44% and 66.67%, respectively. In these controllers all self-connections are excitatory. The time constant averages 1.2393 (std.: 0.3034) and 16.2495 (std.: 9.4701), and the average of biases are 1.5568 (std.: 2.0724) and 0.3492 (std.: 1.0210), in that order. There is a significant difference in the mean of time constants and biases in the studied controllers; i.e. E2 has a tendency to behave in a slower way because of these high time constants. Chapter 8 also discuss this observation.

Parameters	**Strength of parameters**	
	C1	**E2**
w (1;1)	3.3031301	4.266944
w (1;2)	-3.6604936	-8.000000
w (1;3)	-5.8026167	-3.355536
w (2;1)	0.64409778	-3.355536
w (2;2)	1.04792498	4.266944
w (2;3)	-5.7682838	-8.000000
w (3;1)	0.20528219	-8.000000
w (3;2)	-7.92000914	-3.355536
w (3;3)	2.3348314	4.266944
θ (1)	-0.8270765	0.690450
θ (2)	2.56716915	1.155906
θ (3)	2.93021439	-0.798660
τ (1)	1.0	20.113732
τ (2)	1.58057124	5.458366
τ (3)	1.13741345	23.176495
Winput	10.8612781	11.923363
rightMotor	43.512342	48.738291
leftmotor	29.334830	4.478747

Table A.6. Parameter values of the analysed neurocontrollers in Chapter 8. Where $\tau(i)$ is the i-th neuron time constant, $w(j;i)$ is the strength of the connection from the j-th to the i-th neuron, and $\theta(i)$ is a bias term. Winput, rightMotor, and leftmotor represent the magnitude of the connection between the sensor and neurons, the right and the left motor strength, respectively.

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